

Maintenance Strategies for Serial Production Lines Based on Grey Cluster Evaluation and Opportunity Maintenance

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Abstract

To address the issues of “under-maintenance” and “over-maintenance” arising from uneven maintenance resource allocation and considering equipment variability for Serial production line in manufacturing, this study proposes an integrated maintenance strategy that combines grey clustering evaluation with opportunity maintenance. This approach aims to optimize the total system maintenance cost while ensuring equipment reliability. First, an Equipment importance Evaluation Index System is constructed. A Grey Clustering Model based on the Center-Point Mixed Possibility Functions is applied to classify production line equipment into three grey categories: “Secondary,” “Important,” and “Critical.” Subsequently, an opportunity maintenance model is established for critical equipment, targeting minimization of total cost rates while constraining equipment reliability. This model dynamically decides whether to perform synchronized opportunity maintenance on target equipment during repairs of other equipment by introducing an opportunity maintenance reliability calibration threshold, thereby integrating maintenance activities and reducing downtime. The model accounts for the impact of maintenance activities on equipment service life and failure rates, and employs a genetic algorithm for solution. Validation was conducted using an automated packaging line with 10 pieces of equipment from a company as a case study. Results demonstrate that the optimized maintenance strategy establishes differentiated reliability calibration thresholds for each critical piece of equipment. Compared to the original strategy, the total cost rate decreases by 25.7% compared to the original maintenance pattern.

Keywords

Maintenance Strategy, Grey Clustering Model, Opportunity Maintenance, Reliability, Genetic Algorithm.

Introduction

With the advancement of economic globalization and the rapid improvement in industrial technology, manufacturing enterprises have continuously expanded their production scale. Equipment maintenance constitutes a vital component of production management activities, as maintenance schedules directly impact production scheduling, product quality, and costs.

System maintenance strategies encompass a broad scope and can primarily be categorized into group maintenance strategies and opportunistic maintenance

strategies. Liu (2012) investigated a equipment-failure-count- based group maintenance strategy for systems composed of multiple servers, where group maintenance is initiated when the number of failed servers reaches a predetermined threshold. Kermanshachi et al. (2020) established a group maintenance model for multi-component equipment in natural gas pipeline systems, considering variations in maintenance environments and constrained by human resources. However, complex systems often exhibit interdependencies between components. Li et al. (2023) introduced fault chains to describe complex interdependencies among multiple components. They implemented a non-periodic group maintenance strategy for system components, optimizing both maintenance time and maintenance costs.

Research on opportunity maintenance strategies primarily involves multi- component maintenance models. In recent years, maintenance studies on multi- component systems have proliferated, exemplified by the work

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of Keizer et al. (2017) and (de Jonge & Scarf, 2020). On one hand, interactions between components complicate maintenance modeling and optimization. On the other hand, they also present opportunities for maintaining other components, potentially reducing overall system maintenance costs. Zhang & Yang (2020), Zhou & Ning (2021) proposed that opportunity maintenance should be performed if the planned maintenance time falls within a predetermined time window, with the time window itself set as one of the decision variables. Carroll et al. (2019) employed grey system theory to construct time-varying characteristic sequences for rolling bearings based on comprehensive degradation feature indicators, thereby designing residual life prediction functions. Gao & Hao (2021) leveraged grey system theory which demonstrates strong applicability for small-sample analysis—to predict the residual corrosion life of subsea pipelines using grey system models. However, both approaches considered only individual equipment without accounting for the interdependent characteristics among devices within the system.

The aforementioned research on equipment maintenance and system maintenance provides theoretical insights and methodological guidance for this paper. Building upon existing work, it is important to note that most current studies on equipment maintenance strategies are often limited to predetermined reliability thresholds, frequently neglecting the actual operating conditions of equipment. During equipment operation, degradation processes may lead to abnormal functioning that not only reduces production efficiency but also incurs additional operational costs—such as increased energy consumption and expenses resulting from diminished product quality. These costs are frequently overlooked in current research. Therefore, dynamically and rationally considering equipment reliability thresholds can prevent the formulation of empirically based maintenance strategies.

This paper makes a valuable exploration and contribution to the field of maintenance decision-making for multi-device series systems. The main contributions are as follows:

1. This study expands the application paradigm of equipment importance assessment in the optimal allocation of maintenance resources. To address the limitation in traditional research, which often assumes equal importance of equipment in series systems or employs a single criterion for classification, this paper constructs a comprehensive evaluation index system based on grey clustering evaluation. This system integrates the three dimensions including reliability, maintainability, and economy.
2. A dynamic preventive maintenance model is constructed by incorporating a service age reduction

factor and a failure rate increase factor. A genetic algorithm is employed to solve the strategy model. This approach not only saves considerable time and effort but also optimizes the accuracy and stability of the model.

System Description

This paper conducts a systematic analysis of production operation and maintenance strategies for serial systems in manufacturing, examining maintenance approaches for handling unexpected equipment failures and scheduled maintenance plans.

The current maintenance strategy in manufacturing primarily relies on corrective maintenance supplemented by scheduled maintenance. While this approach facilitates planning management, it suffers from issues such as uneven resource allocation and insufficient consideration of equipment variability. This often leads to either under-maintenance or over-maintenance, adversely affecting overall equipment reliability and operational efficiency. Furthermore, maintenance intervals are predominantly set based on empirical judgment rather than scientific evidence derived from equipment condition and failure data, making it difficult to adapt to dynamically changing failure characteristics.

Description of Maintenance Strategies Based on Grey Cluster Evaluation and Opportunity Maintenance

Given the shortcomings of current maintenance strategies in manufacturing and the inherent complexity of serial production line structures—which typically encompass multiple distinct pieces of equipment—it is necessary to first establish a scientific indicator system based on the importance of each equipment. Subsequently, using grey cluster evaluation, equipment should be categorized into three grey categories: “Secondary Equipment,” “Important Equipment,” and “Critical Equipment”. This approach enables the rational allocation of maintenance resources.

Optimizing maintenance strategies for the identified critical equipment. Unlike traditional scheduled maintenance approaches, this requires determining which equipment and components require maintenance activities for the $(i - 1, i \geq 2)$ th maintenance cycle. During the i -th maintenance cycle, a preventive overhaul (restoring to like-new condition) is performed. Thus, a complete maintenance cycle for the equipment

encompasses the preceding $i - 1$ maintenance cycles and the i -th preventive overhaul cycle. During each maintenance cycle or preventive overhaul cycle, maintenance activities or preventive overhauls are initiated when the equipment reliability drops to the corresponding threshold.

However, the aforementioned strategy fails to account for the time window effect during equipment downtime for maintenance. Therefore, the concept of opportunity maintenance is introduced to optimize the overall maintenance strategy for serial production line equipment. Opportunity maintenance represents an improved approach to multi-system maintenance strategies. It occurs when preventive maintenance activities on one subsystem within the system also create maintenance opportunities for other subsystems. At this point, all individual equipment meeting the maintenance opportunity criteria can undergo simultaneous maintenance activities. This achieves the dual objectives of sharing maintenance costs and reducing downtime.

Research Hypothesis

Based on the actual conditions of model construction, the following assumptions are made:

1. The enterprise possesses sufficient maintenance personnel and resources to promptly address failures when they occur.
2. The degradation and failures of each piece of equipment follow a two-parameter Weibull distribution, and defects arising in different equipment are mutually independent and do not influence one another.
3. During maintenance activities, existing defects in each piece of equipment can be detected and repaired, and the time required for defect repair is significantly shorter than the maintenance time and can be considered negligible.
4. Maintenance activities represent imperfect repairs that do not fully restore equipment service life. When reliability reaches a predetermined threshold, preventive major maintenance (perfect repair, restoring equipment to new condition) is performed, fully restoring the equipment's reliability.
5. If equipment fails between two preventive maintenance intervals, minimal repairs are performed to restore equipment performance without altering reliability.

Basic Model Parameters and Variables

The basic parameters and variables used in this model are as follows (Tab. 1).

Table 1
Model Parameters and Explanations

Parameter	Explanatory Notes
k	Represents the serial number of critical equipment, where $k = 1, 2, 3, \dots$
i	Represents the i -th maintenance cycle for equipment, where $i = 1, 2, 3, \dots$
t_k	Represents the random value of critical equipment k at any given moment.
$f(t_{k,i}), F(t_{k,i})$	The probability density function (PDF) and cumulative distribution function (CDF) of critical equipment k during the i -th cycle, where $k = 1, 2, 3, \dots, i = 1, 2, 3, \dots$
$R(t_{k,i})$	Represents the reliability function of critical equipment k during the i -th cycle, where $k = 1, 2, 3, \dots, i = 1, 2, 3, \dots$
$\lambda(t_{k,i})$	Represents the failure rate of critical equipment k during the i -th cycle, where $k = 1, 2, 3, \dots, i = 1, 2, 3, \dots$
$T_{k,i}$	Represents the total preventive maintenance cycle time for critical equipment k , where $k = 1, 2, 3, \dots, i = 1, 2, 3, \dots$
a_i	Decay factor for the service life of representative equipment during the i -th cycle.
b_i	Representative equipment failure rate increment factor within the i -th cycle.
$-LnR_{k,i}$	Represents the cumulative failure risk of critical equipment k during the i -th maintenance period.
C_{it}	Maintenance cost per unit of downtime for the production line equipment during the i -th cycle
C_{iw}	The cost of lost revenue per unit of downtime for the production line equipment during the i -th cycle.
$MTTR_k$	The minimum time required to repair equipment k in the event of a sudden failure.
t_{pk}	The time required to perform one maintenance cycle on critical equipment k .
$E_{k,i}^d$	Number of components representing critical equipment k that fail during the i -th maintenance period.
$C_{k,i}^d$	Unit price per component representing the number of failures of critical equipment k during the i -th maintenance period.

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$R_{k \min}$	Represents the minimum reliability required for critical equipment k to operate; this paper adopts 0.5.
Δr_k	Calibration threshold for opportunity maintenance reliability corresponding to critical equipment k .
wiersz 19 Δt_k	Representing the time domain for individual equipment where critical equipment k meets the opportunity maintenance condition and maintenance activities can be performed.
wiersz 20 $O(k, t_n)$	The method adopted for preventive maintenance activities for critical equipment k at time t_n .
$C_{ws,k}$	Represents the maintenance costs incurred by critical equipment k due to opportunity maintenance activities.
C_{ws}	Equipment maintenance costs incurred by the entire production line due to opportunity maintenance activities.
T_{jt,t_n}	Represents the planned downtime for the entire production line during the t_n time period.
T_{ft,t_n}	Unplanned downtime for the entire production line during the t_n time period.
T_{tx}	The total downtime of the production line .
C_{tx}	The total labor costs of the production line.
C_{xr}	The total maintenance cost of the production line.
T_{yx,t_n}	Represents the total uptime of the entire production line during the t_n time period.
T_{yx}	Representing the total uptime of the entire line during a single opportunity maintenance cycle.
T_{cr}	The total time required for one opportunity to perform maintenance during the normal operation cycle of the entire production line.
$\min f(\Delta r_k)$	Representing the objective function of minimum cost rate with Δr_k as the independent variable.

Establishment and Optimization of Maintenance Strategy Model

Based on the strategy outlined in the previous section, the first step involves categorizing the s devices within the serial line system according to their criticality and establishing corresponding maintenance plans for the identified critical equipment.

Equipment Importance Classification Based on Grey Clustering Evaluation

Given the complexity of the entire production line and the varying performance characteristics of its individual equipment, this paper proposes to evaluate the importance of each piece of equipment based on three key indicators: Reliability Factors, Maintainability Factors, and Economic Factors [?] (Zhao et al., 2019). This approach draws upon the assessment criteria outlined in the literature regarding Equipment importance Classification.

This paper adopts the aforementioned three factors as primary assessment indicators for evaluating equipment maintenance importance. Ultimately, six secondary assessment indicators are defined as follows (Tab. 2):

Table 2
Equipment importance Classification Indicators

No.	Primary Assessment Indicators	Secondary Assessment Indicators
1	Reliability Factors(V1)	Equipment Failure Frequency (v1) [9] (Liu, 2009) Security Implications in Production Environments (v2) [3] (Cui et al., 2016)
2	Maintainability Factors(V2)	Maintenance/Repair Difficulty Level (v3) [11] (Peng et al., 2017) Repairability (v4) [2] (Chen & Cai, 2002)
3	Economic Factors(V3)	Equipment Maintenance Costs(v5) Impact of downtime losses(v6)

To ensure the accuracy and objectivity of the comprehensive assessment, this paper proposes to evaluate the assessment indicators using a combination of quantitative and qualitative analysis. This involves using raw maintenance data to reflect corresponding evaluation grades. Standardizing the obtained scores yields the following results (Tab. 3).

Based on the table above (Tab. 3), the matrix A for each device regarding each clustering metric x_{ij} is obtained.

The grey clustering evaluation model based on the Center-Point Mixed Possibility Functions is suitable for scenarios where points can be relatively easily judged as belonging most likely to each grey category, but

Table 3
 Equipment Performance Metrics Scoring

No.	Name	Indicator (v1)	Indicator (v2)	...	Indicator (v6)
1	Equipment 1	x_{11}	x_{12}	...	x_{16}
2	Equipment 2	x_{21}	x_{22}	...	x_{26}
...	...	...	...	...	...
s	Equipment s	x_{s1}	x_{s2}	...	x_{s6}

where the boundaries between grey categories are unclear. Therefore, this paper adopts the Center-Point Mixed Possibility Functions.

Based on field investigations and expert interviews, the fundamental values λ_j^k for each grey category can be determined, enabling the derivation of the possibility function $f_j^n(\cdot)$ ($j = 1, 2, 3, 4, 5, 6; n = 1, 2, 3$) for indicator j regarding grey type k .

The grey weighted clustering coefficient matrix D is obtained from $\sigma_i^n = \sum_{j=1}^m f_j^n(x_{ij}) \cdot v_j$.

This enables the classification of equipment into distinct grey categories, thereby determining the importance level of each piece of equipment and identifying k critical pieces of equipment. This provides a basis for subsequent maintenance strategy modeling.

Establishing a Maintenance Strategy Model for Serial Production Lines Based on Opportunity Maintenance

Based on the k critical pieces of equipment identified in the previous section, A maintenance strategy model will be established, which targets the maintenance cost of the entire production line and constrains the reliability of equipment operation. Incorporating the concept of opportunity maintenance, the formula for calculating the maintenance cost incurred by k pieces of equipment due to preventive maintenance activities within a single opportunity maintenance cycle is as (3) follows:

$$C_{ws,k} = \begin{cases} 0 & O(k, t_n) = 0 \\ C_{iw} \cdot [(-\ln R_{k \min})MTTR_k + t_{pk}] + E_{k,i}^d \cdot C_{k,i}^d & O(k, t_n) = 1 \\ C_{iw} \cdot [(-\ln(R_{k \min} + \Delta r_k))MTTR_k + t_{pk}] + E_{k,i}^d \cdot C_{k,i}^d & O(k, t_n) = 2 \\ C_{iw} \cdot (-\ln R_{k \min})MTTR_k + E_{k,i}^d \cdot C_{k,i}^d + C_{rk} \cdot t_{rk} & O(k, t_n) = 3 \end{cases} \quad (1)$$

$O(k, t_n)$ represents the preventive maintenance approach adopted by equipment k at time t_n . $O(k, t_n) =$

0 indicates no preventive maintenance is performed; $O(k, t_n) = 1$ indicates maintenance activities are conducted; $O(k, t_n) = 2$ indicates that when other equipment undergoes maintenance or repair, equipment k undergoes maintenance or repair as an opportunity maintenance; $O(k, t_n) = 3$ indicates reliability has fallen below the minimum threshold, necessitating maintenance or repair activities.

To simulate machinery operation under real-world conditions and achieve more accurate failure prediction, the following section introduces the service life decay factor parameter a_i and the failure rate increase factor parameter b_i into the failure distribution function. The original two-parameter Weibull reliability function is then rewritten as the reliability $R_i(t)$ after maintenance over a period of T_i :

$$R_i(t) = \begin{cases} \exp \left[- \left(\frac{t}{\alpha} \right)^\beta \right] & i = 1 \\ b_i \cdot R_{i-1}(t - a_i T_i) & i > 1, \quad i = 2, 3, 4, \dots \end{cases} \quad (2)$$

Referencing the value assignment methods in relevant literature [?], this paper proposes to adopt an empirical approach to assign values for the two maintenance improvement factors mentioned above, as follows:

$$a_i = \frac{i}{4i + 7}, \quad b_i = \frac{12i + 1}{11i + 1} \quad (3)$$

From equation (2), the subsequent result follows directly.

$$\begin{aligned} \exp \left[- \int_0^{t_{1,k}} \lambda_{1,k}(t) dt \right] &= \exp \left[- \int_{t_{1,k}}^{t_{2,k}} \lambda_{2,k}(t) dt \right] = \dots \\ &= \exp \left[- \int_{t_{i-1,k}}^{t_{i,k}} \lambda_{i,k}(t) dt \right] = R_{k,m} \end{aligned} \quad (4)$$

Obtained through transformation,

$$\int_{t_{i-1}}^{t_i} \lambda_{i,k}(t - a_i T_i) dt = -\ln [b_i \cdot R_i(t)] \quad (5)$$

The cumulative failure risk $\int_{t_{i-1}}^{t_i} \lambda_{i,k}(t - a_i T_i) dt$ for equipment k over the $T_{i,k}$ cycle period can be derived as $-\ln [b_i \cdot R_i(t)]$. The maintenance cost incurred by production line downtime due to opportunity maintenance activities within a single opportunity maintenance cycle time can be expressed as:

$$C_{ws} = \sum_{n=1}^N \sum_{k=1}^K C_{ws,k} \quad (6)$$

The downtime within the t_n period can be expressed as:

$$T_{jt,t_n} = \max_{1 \leq M \leq K} (t_{pk,t_n}, t_{rk,t_n}) \quad (7)$$

Similarly, the total downtime can be expressed as:

$$T_{tx} = \sum_{n=1}^N (T_{jt,t_n} + T_{ft,t_n})$$

$$= \sum_{n=1}^N \left[\max_{1 \leq M \leq K} [(t_{pk,t_n}, t_{rk,t_n}) +] \right. \\ \left. (-\ln R_{k \min}) \cdot MTT R_k \right] \quad (8)$$

The labor cost loss can be expressed as:

$$C_{tx} = C_{it} T_{tx} = C_{it} \sum_{n=1}^N (T_{jt,t_n} + T_{ft,t_n}) \quad (9)$$

Therefore, from Equations (6), (9) the total maintenance cost of the line is given by:

$$C_{xr} = C_{ws} + C_{tx} = \sum_{n=1}^N \sum_{k=1}^K C_{ws,k} + C_{it} \sum_{n=1}^N T_{tx,t_n} \quad (10)$$

The normal operating time of the production line can be expressed as:

$$T_{yx,t_n} = \min_{1 \leq M \leq K} (t_{(R_{k \min})k,t_n}, t_{(R_{k \min} + \Delta R_k)k,t_n}) \quad (11)$$

$$T_{yx} = \sum_{n=1}^N T_{yx,t_n} \quad (12)$$

Finally, establish a planning model constrained by the minimum reliability $R_{k \min}$ and targeting the minimum cost rate:

$$\begin{cases} \min f(\Delta r_k) = \frac{C_{xr}}{T_{cr}} = \frac{\sum_{i=1}^k C_{ws,k} + C_{it} \sum_{n=1}^N T_{tx,t_n}}{\sum_{n=1}^N T_{yx,t_n} + \sum_{n=1}^N T_{tx,t_n}} \\ \text{s.t. } R_{k,t_n}(t) \geq R_{k \min}, \quad k = 1, 2, 3 \dots \\ 0 \leq \Delta r_k < 1 - R_{k \min}, \quad k = 1, 2, 3 \dots \\ T_{cr} > 0, \quad t_n > 0, \quad n = 1, 2, 3 \dots \end{cases} \quad (13)$$

Case Analysis

This paper uses a company's automated packaging line as an example. The line is a serial system comprising ten pieces of device of different types.

After collecting and processing data from each device on the line, a matrix A is obtained for each device regarding the clustering metrics x_{ij} , as shown below:

$$A = (x_{ij}) = \begin{bmatrix} 0.021 & 0.543 & 0.712 & 0.898 & 0.444 & 0.833 \\ 0.091 & 0.293 & 1.000 & 0.832 & 0.803 & 0.833 \\ 0.016 & 0.070 & 0.475 & 0.823 & 0.248 & 0.667 \\ 0.009 & 0.060 & 0.407 & 0.859 & 0.607 & 0.667 \\ 0.697 & 0.457 & 0.765 & 0.929 & 0.624 & 0.833 \\ 0.045 & 0.912 & 0.247 & 0.840 & 0.158 & 0.667 \\ 1.000 & 1.000 & 0.827 & 1.000 & 0.641 & 1.000 \\ 0.112 & 0.151 & 0.367 & 0.868 & 0.248 & 0.667 \\ 0.091 & 0.334 & 0.944 & 0.832 & 0.803 & 0.833 \\ 0.010 & 0.524 & 0.735 & 0.888 & 1.000 & 1.000 \end{bmatrix} \quad (14)$$

Based on field investigations and expert interviews, the fundamental values λ_j^k for each grey category have been determined as follows (Tab. 4):

Table 4
The Fundamental Values

No.	Turning Point λ_j^1	Turning Point λ_j^2	Turning Point λ_j^3
1	0.105	0.209	0.314
2	0.217	0.434	0.651
3	0.329	0.658	0.987
4	0.850	0.900	0.950
5	0.400	0.575	0.750
6	0.700	0.775	0.850

The weighting of each indicator is determined based on input from interviewed experts and on-site personnel.

$$v_1 = 0.211, \quad v_2 = 0.132, \quad v_3 = 0.138, \quad v_4 = 0.126,$$

$$v_5 = 0.198, \quad v_6 = 0.195$$

The grey weighted clustering coefficient matrix D can be obtained as:

$$D = (\sigma_i^k) = \begin{bmatrix} 0.360 & 0.359 & 0.282 \\ 0.297 & 0.089 & 0.614 \\ 0.813 & 0.061 & 0.126 \\ 0.643 & 0.195 & 0.162 \\ 0.037 & 0.486 & 0.477 \\ 0.742 & 0.000 & 0.258 \\ 0.126 & 0.190 & 0.684 \\ 0.844 & 0.036 & 0.121 \\ 0.272 & 0.132 & 0.596 \\ 0.211 & 0.241 & 0.548 \end{bmatrix} \quad (15)$$

From Equation (15), it can be determined that the critical equipment belonging to grey Category 3 includes Equipment 2, Equipment 7, Equipment 9, and

Equipment 10 – these four pieces of equipment. Marked respectively as Device1, Device2, Device3, Device4.

Collect data on the failure dates of critical equipment on the company's packaging lines during the period from January 2023 to June 2024 (Tab. 5).

Table 5
Device failure interval table

No.	Failure interval of Device1 (h)	Failure interval of Device2 (h)	Failure interval of Device3 (h)	Failure interval of Device4 (h)
1	1074	1342	529	2123
2	1286	376	425	2372
3	1253	84	269	1735
4	1960	279	364	1198
5	1022	313	638	1807
6	1723	1011	35	1526
7	1011	941	401	1661
8	1514	667	521	1636
9	805	245	144	
10	700	367	542	
11	652	149	213	
12	941	642	83	
13	624	431	288	
...	...	...	...	
27		158	...	
...			...	
35			1027	

The shape and scale parameters of the four critical pieces of equipment (Tab. 6), and the corresponding maintenance parameters (Tab. 7).

Table 6
Parameters of the Two-Parameter Weibull Distribution

No.	Name	Shape (β)	Scale (α)
1	Device 1	3.013	1257.384
2	Device 2	1.239	543.816
3	Device 3	1.284	428.327
4	Device 4	5.596	1898.36

The variable in equation (13) is the opportunity maintenance reliability calibration threshold Δr_k . The specific solution logic is as follows:

1. Set the corresponding Δr_k for each piece of equipment and determine the relationship between Δr_k and $R_k(t) - R_{k \min}$.

Table 7
Equipment Maintenance Parameters

No	Name	$C_{k,i}^d$ (rmb)	C_{it} (rmb/h)	C_{iw} (rmb/h)	MTTR _k (h)	t_{pk} (h)	T_{rk} (h)
1	Device 1	200	19	9.5	0.5	2.5	5
2	Device 2	400	19	9.5	0.5	1.5	6
3	Device 3	200	19	9.5	0.5	1	4
4	Device 4	400	19	9.5	0.5	2	6

2. Determine the timing t_n for the n -th preventive maintenance of the packaging line. Let M denote the total number of critical devices within the packaging line. $t_n = \min(t_{1n}, t_{2n}, \dots, t_{Mn})$. When $n = 1$, $t_{11} = T_{11}$.
3. Calculate C_{xr} and T_{yx} .
4. Calculate the next preventive maintenance timing $t_{k(n+1)}$ for device k . Then, using Step 1, determine the timing t_{n+1} for the $(n + 1)$ -st maintenance of the packaging line. Repeat Steps 2 to 4 until $t_n > T$.
5. Continuously adjust Δr_k and repeat the above steps until the maintenance cost corresponding to the optimal opportunity threshold is obtained.

Using a GA to solve the predictive maintenance model for the critical equipment of the packaging line, the known parameters of each critical piece of equipment are input into the established model. The specific implementation process is as follows:

1. Setting the Initial Population

Population individuals are characterized through a specific encoding mechanism. Within the opportunity preventive maintenance model constructed in this paper, individuals are defined as the opportunity preventive maintenance thresholds (Δr_k) for each subsystem. The program randomly generates n initial feasible solutions, denoted as $\Delta r(i)$, each $\Delta r(i)$ representing an independent individual. These individuals collectively form an initial population of size n which $P_0 = [\Delta r(1), \Delta r(2), \dots, \Delta r(i)]$.

2. Calculating Individual Fitness

The fitness function serves as the core criterion for evaluating and selecting individuals, typically constructed in close association with the objective function. Its specific form may be defined as the objective function's raw value, its negative, or its reciprocal. In this study, fitness is defined as a mapping of the total maintenance cost function $C(\Delta r_1, \Delta r, \dots, \Delta r_M)$. Aligned with the opti-

misation objective, a lower total maintenance cost indicates higher fitness for the corresponding individual, signifying superior solution quality.

3. Screening the initial population

For initial population screening, the selection operator implements a ‘survival of the fittest’ mechanism. Under this mechanism, an individual’s probability of being passed on to the next generation is positively correlated with its fitness value: individuals with higher fitness values have a greater probability of retention, while those with lower values have a smaller probability. This paper employs roulette wheel selection to select the fittest individuals within the population. Concurrently, by setting crossover probabilities P_c and mutation probabilities P_m , the genetic iteration and renewal of the population are driven, thereby continuously generating new generations to achieve cyclical optimisation.

4. Iteration Completion

When the algorithm reaches the predefined maximum iteration threshold, the system triggers the termination condition and halts computation, subsequently outputting the final solution result.

The initial population size is set to $P_0 = 50$, the maximum iteration count to $G_{\max} = 400$, the crossover probability to $P_c = 0.6$, the mutation probability to $P_m = 0.01$, and the variable range to $[0, 1 - R_{k \min}]$. The solution results are shown in the figure below (Fig. 1).

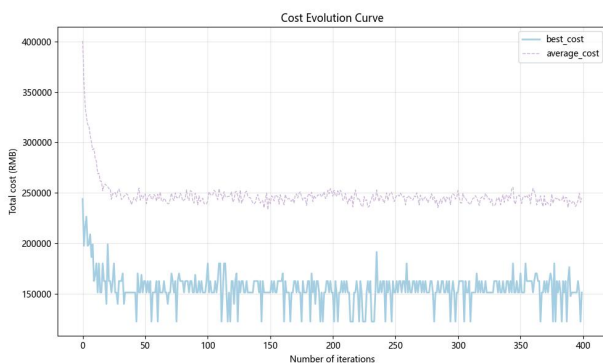


Fig. 1. Cost Evolution Curve

The results from the figure show that after 100 iterations, the results stabilize, with the optimized average minimum value being . The reliability calibration thresholds for each major piece of equipment—that is $\Delta r_k = (0.067, 0.078, 0.051, 0.238)$, the minimum reliability levels for updated critical equipment are $R_{k \min} = (0.567, 0.578, 0.551, 0.738)$. Preventive maintenance can be performed when any equipment falls below its corresponding $R_{k \min}$.

Following the implementation of the newly formulated maintenance strategy for critical equipment on the packaging line, the simulated operational performance is as follows (Fig. 2):

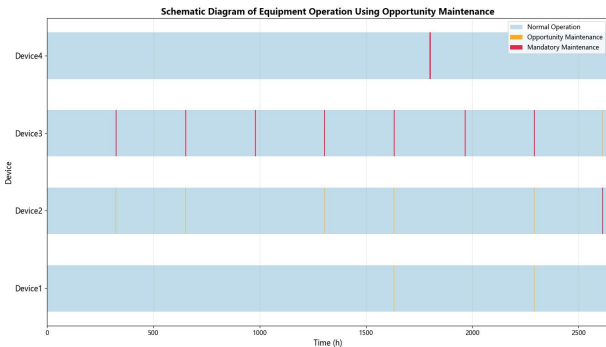


Fig. 2. Line Simulation Operation

To visually compare results before and after optimization, this paper uses a factory production time of 2640 (h). After considering opportunity maintenance, the total maintenance costs for the packaging line have been significantly reduced. The specific comparison details are as follows (Tab. 8).

Table 8
Comparison Between Original Strategy and Optimized Maintenance Strategy

Maintenance Strategy Metrics	Original Strategy	Optimization Strategy
Average Equipment Downtime (h)	386.5	325.75
Average Equipment Availability (%)	83.9	87.7
Average Reliability (%)	76	86
Total Cost (in thousands)	195.3	145.3
Total Cost Rate Decrease (%)	25.7%	

Conclusion

This paper constructs an evaluation system based on multi-dimensional indicators such as reliability, maintainability, and economic efficiency. The grey clustering model is then employed to classify equipment by importance and identify critical assets. Building upon this foundation, an opportunity maintenance mechanism is introduced. By integrating equipment reliability

thresholds and time windows, a serial line maintenance model targeting minimized maintenance costs is established and solved using a genetic algorithm. Case studies demonstrate that the proposed strategy significantly reduces total system maintenance costs while ensuring equipment reliability, thereby enhancing equipment availability and operational efficiency. This validates the model's effectiveness and practicality.

Although the proposed maintenance strategy demonstrates excellent optimization results in both theoretical and simulation aspects, certain limitations remain. Future research could further explore the following directions: In actual production, uncertainties exist in equipment operating conditions, maintenance resources, and external environments. Future work could integrate reinforcement learning or stochastic programming methods to develop dynamic adaptive maintenance decision models. While this study focuses on cost minimization, future research could incorporate multi-objective criteria such as energy efficiency, quality, and carbon emissions to establish a more comprehensive maintenance decision framework. With advancements in industrial IoT and big data technologies, real-time monitoring data could be further integrated to enable digital twin-based predictive maintenance and intelligent operations and maintenance.

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