South Asian Journal of Marketing & Management Research (SAJMMR)
ISSN: 2249-877X Vol. 14, Issue 5-6, May-June 2024 SJIF 2022 = 7.911
A peer reviewed journal

MULTI-OBJECTIVE OPTIMIZATION OF ACCURATE PRODUCTION AND MAINTENANCE PLANNING USING PSO ALGORITHM, IN ORDER TO REDUCE PRODUCTION AND WAREHOUSING COSTS

Mahdi Hatami*; Mahdi Kabiri Naeini**

*M.Sc. Graduate,
Payame Noor University, Asaluyeh, IRAN
Email: eng.hatami65@gmail.com

**Assistant Professor,
Payame Noor UniversityYazd, IRAN
Email id: m_kabirinaeini@yahoo.com

DOI: 10.5958/2249-877X.2024.00003.8

ABSTRACT

Production planning is one of the main factors affecting real productivity and efficiency. Effective scheduling programs greatly improve the performance of production systems. In this research, an extended multi-objective optimization model is defined. The proposed model includes minimizing service time, production costs, and minimizing maintenance costs. The advantage of the proposed model is that it is defined based on the Poisson distribution of the reduction of the number of failures, also the defined Gaussian model can determine the optimal production capacity according to the previous data. In this regard, the function of the second goal is to reduce maintenance costs. High accumulation of inventory increases the cost of the organization or industrial plant and hides the problems, and keeping the inventory at the optimal level reveals the manageable problems that can be corrected in the organization and production. The proposed model is finally solved and compared using a multi-objective suspended particle swarm optimization algorithm and genetics for a numerical example.

KEYWORDS: *Production Planning, Warehousing, Maintenance, Mpso Algorithm, Genetic Algorithm.*

INTRODUCTION

Considering that accurate planning to reduce production and inventory costs is of great importance, this research has endeavored to address this gap and provide an optimal solution for accurate planning to reduce production and inventory costs.

In this research, a multi-objective optimization problem is considered, the objective functions of which are time, cost, maintenance, and the number of system failures over time. An important issue that has been considered is accurate maintenance. In accurate maintenance, dynamic strategies are considered. In this case, the device's lifetime is also considered as a variable and is taken into account in the calculations. The longer the life of a device, the more expensive its maintenance will be. Also, the probability of random failure is also taken into account in the calculations. For this purpose, the generalized Weibull function is used. The difference between this function and the standard Weibullfunction is that in the generalized function, a new variable is also added to the problem, which results in more control over the problem. Adding a parameter to the distribution function allows the maintenance problem to be defined more accurately.

The objective function is the number of failures in a time period. The fewer the failures, the more efficiently production planning is carried out and, as a result, the model's performance improves. The proposed function is defined based on the Poisson distribution. The Poisson process is a point counting process that is defined around the occurrence of random events on a time interval or a spatial distance. In examining this process, the time between two successive events is specified by an exponential distribution, and separate time intervals are considered independent of each other.

While reducing production time and volume can improve inventory management, this issue needs to be considered more carefully. Therefore, a new optimization function is defined for this purpose. In warehousing, the number and variety of raw materials and manufactured parts are not the same. For example, to produce a product, M raw materials may be needed, all of which are necessary for production. Therefore, a general relationship should be developed for this issue that is valid regardless of the product. In the proposed method, it is assumed that optimal production has a Gaussian distribution. In other words, based on the available information, the optimal production quantity of a product in a factory will be K. If the factory's production exceeds this amount, it may have problems with inventory management. In this research, the creation of more warehouse space is not considered, as this issue needs to be examined from various aspects. On the other hand, the Gaussian distribution function used is an effective solution for this issue, which can define optimal production in a range.

One of the important issues facing production units is reducing production and maintenance costs. Since the failure of production systems cannot be definitively predicted, it is therefore necessary to consider probabilistic methods. In addition, inventory management also has many complexities, because some warehouses are actually intermediaries between production and consumption, and both production and consumption aspects must be considered in their formulation. Both production and maintenance are closely related and need to be considered comprehensively and simultaneously.

Production planning is one of the main factors affecting actual productivity and efficiency. Effective plans greatly improve the scheduling of production system performance. Wear and tear, damage to the device with continuous use, is inevitable. Maintenance is only needed if a failure occurs. Therefore, there are few studies on this strategy due to the irreparable economic losses.

Careful planning and maintenance play a very important role in production as they can help increase production efficiency and product quality. Inventory management allows the production center to better meet the needs of users.

In this research, an optimization problem is defined that considers two important parameters: First: reducing maintenance time, second: reducing maintenance costs. In the defined relation, the device's lifetime is also considered as a probabilistic variable, which makes it possible to perform maintenance accurately and effectively. In addition, a function is introduced to reduce the number of failures during the device's lifetime.

Literature Review

Hosseini et al. (1) studied the integrated production and maintenance planning problem. This problem has two objective functions. The first objective function is the total system cost, which includes all cost factors of production. The second objective function is the level of customer dissatisfaction, which increases due to delays in timely demand fulfillment. Then, considering that this problem is of the NP-Hard type, a solution method based on the non-dominated sorting genetic algorithm - revision was presented.

SajjadiNejad et al. (2) presented a non-periodic preventive maintenance and repair (PM) scheduling model for multi-component (series-parallel) systems, based on the maximum availability of system components. Also, since the proposed model has a complex structure, a genetic algorithm was used to solve it.

Gholamrezaee et al. (3) introduced a multi-product and multi-objective production planning model with fuzzy parameters and time value of money based on inventory level, workforce level, machine capacity and storage space. The proposed model maximizes sales profit, minimizes maintenance costs and backorders, and changes in manpower levels.

Ahmadinejad et al. (4) examined a practical linear programming model to minimize production costs in the Adrang furniture workshop. The objective function was to reduce the cost of furniture production.

Yang et al. (5) studied a system under two common failure modes, degradation-based failure and sudden failure. This system operates in a random environment where external shocks are introduced according to a Poisson process. The impact of shock damage on system failure is twofold: (a) it increases the hazard rate of sudden failure; (b) it causes a sudden increase in degradation. The objective of the paper is to jointly optimize the replacement interval, monitoring interval, and reliability metric to minimize the expected cost per unit time.

Poppe et al. (6) investigated condition-based maintenance in a monitored component with preventive periodic maintenance and corrective maintenance. Two thresholds were implemented at the degradation level to determine the service time. Both thresholds are optimized to minimize the total expected maintenance costs of the monitored monitor or to minimize the downtime of the device due to maintenance in the monitored component.

Martinod et al. (7) proposed a stochastic optimization model to minimize the total maintenance cost of complex systems over the long term. The proposed work is based on the following approaches: and a clustering method for maintenance actions to reduce the total maintenance cost of the complex system. This work evaluates each maintenance policy and evaluates its impact on incomplete maintenance actions. Finally, the proposed optimization model is applied to a numerical example that focuses on urban passenger aerial ropeway transportation systems, where the current maintenance policy was evaluated.

Yang et al. (8) investigated a new two-phase preventive maintenance policy for a single-component system with the objective of maximizing revenue from performance-based contracting. The system enters a faulty state before failure and generates a signal indicating it. The results showed that the proposed maintenance policy outperforms some existing maintenance policies in terms of net revenue.

Rifai et al. (9) presented a ranked non-dominated sorting genetic algorithm optimization for scheduling multi-loading/unloading diagrams and injected shortcuts in re-entrant feature spaces. This model was formulated to identify the closest optimal trade-off solutions that can meet both objectives of minimizing production time and early completion. The goal was to simultaneously determine the best machine assignment and job sequence to meet both objectives. A set of test problems was analyzed to assess the effectiveness, efficiency, and diversity of the proposed approaches compared to the standard NSBBO and NSGA-II. The results showed that the NSBBO trapezoid model performs well and is comparable to existing models. Therefore, it can be said that the developed NSBBO and its variants are suitable alternatives for achieving two-objective satisfaction in the FMS rescheduling problem.

Yu et al. (10) designed a two-phase opportunistic maintenance framework based on defect information, which integrates production expectation characteristics into the decision-making process. In the first phase, a limited number of inspections were performed to reveal the faulty state, followed by incomplete preventive repair. In the second phase, no maintenance action is taken until a scheduled maintenance window (deferred maintenance) or production expectations (opportunistic maintenance) are reached.

Mathematical Modeling

The proposed model is as follows: A set of n jobs represented by the set J {J={J1, J2, …, Jn} and a set of m machines represented by M and M={M1, M2, … Mm}. Each job Ji has a sequence of operations ni {Oi,1, Oi,2, …, Oi,ni}. Processing is done sequentially according to a predetermined priority constraint. The model has the characteristics of a flexible processing path, which means that at least one operation can be processed on multiple machines and the processing time of the same operation on different machines is different. Therefore, two subproblems are considered:

(1) Machine Selection Problem (MS): Selecting an appropriate machine Mk for operation Oi, j from the optional machine set Mopt

(2) Job Sequencing Problem: Since at least one machine can process multiple jobs or operations, the processing sequence of operations on the machine must be optimized. When changing jobs with the machine (replacing a job or different operations of a job), the job generally goes through the stages of unloading, transportation, loading, calibration, and so on. The time occupied here is called setup time. When setting up the machine for different jobs, it is assumed to be different and the setup time should not be considered in the machine running time. In addition, the setup time of adjacent operations on a machine depends on their similarity, that is, the more similar two workpieces are, the shorter the setup time (drawing the setup time at the beginning of the next operation). This means that the processing sequence affects the setup time and then affects the overall scheduling and maintenance time.

Reliability-based Maintenance Scheduling for Multi-Machine Production Systems with Heterogeneous Failure Distributions

Reliability is an important indicator for evaluating the ability of a machine to perform an operation. Degradation, one of the most important factors affecting machine reliability, is inevitable with increasing age of the machine. To prevent machine failure, reliability for performing the corresponding maintenance activity should be analyzed. Maintenance activities play an important role in production. In other words, the activity determines the specific start time and duration required for maintenance at different reliability intervals (e.g., accurate maintenance). The probability distribution of failures in different types of machines is different due to their specific characteristics. Most machines for processing workpieces in this research are electromechanical equipment whose probability of failure is close to the Weibull distribution. The probability density function of failure fk(Zk) of machine Mk at operating time Zk is as follows [1]:

(1)

$$f_k\left(Z_k\right)=\frac{\beta_k}{\eta_k}\left(\frac{Z_k}{\eta_k}\right)^{\beta_k-1}\exp\left(\left(\frac{Z_k}{\eta_k}\right)^{\beta_k}\right)\quad Z_k\geq 0$$

$$(2)\,R_k\left(Z_k\right)=1-\int_0^{Z_k}f_k\left(Z_k\right)dZ_k$$

Since βk and ηk are related to the effective age of the machine (operating time), Zk should be analyzed before examining reliability. The machine cannot be returned to a new desired state after maintenance. Therefore, it is assumed that the age reduction factor pk of Mk is constant. If the effective age of Mk is Zky before the maintenance period yk is performed, the effective age Zk1 for the first maintenance (i.e., y = 1) is the total processing time of operations on the machine. After y years of maintenance, the effective age of the machine can be expressed as Zky = (1-pk) Zky. In addition, the effective age curves Zk of the machine with calendar time t are shown in Figure (1). Based on the physical phenomenon of machine deterioration, it is proposed that reliability can be considered in three parts R, Y, and G with different failure frequencies or probabilities. In each region, the maintenance activity is different, as shown in Figure (2), where the reliability thresholds for regions Y and R areRy and Rr, respectively. Accurate maintenance activities are entered into the dispatching schedule using a dynamic strategy. When considering processing Oi, j, the processing time is added to the current age of the machine (virtual age, called t) to calculate the reliability value (Rk (t)).

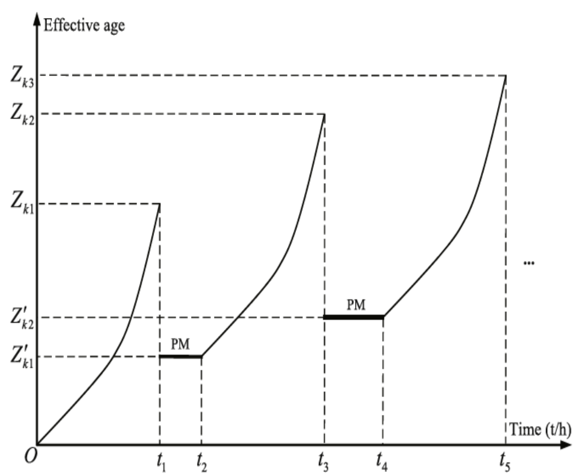

Figure 1.Effective device lifespan

In total, there are three scenarios for different reliability values related to accurate maintenance activities:

(1) If the reliability Rk(t') falls in the G region, no maintenance activity is performed.

(2) If the reliability Rk(t') is in Y, a repair and delay progression selection factor YZ is introduced, which is a random number between zero and one. AM activity is performed before Oi, j. Otherwise, the activity is performed after oi, j. YZ can bring the flexibility of maintenance activities closer to actual production.

(3) If the reliability Rk(t') is in R, the AM activity must be performed before Oi, j, and then the reliability value R is calculated after the machine is finished with Oi, j.

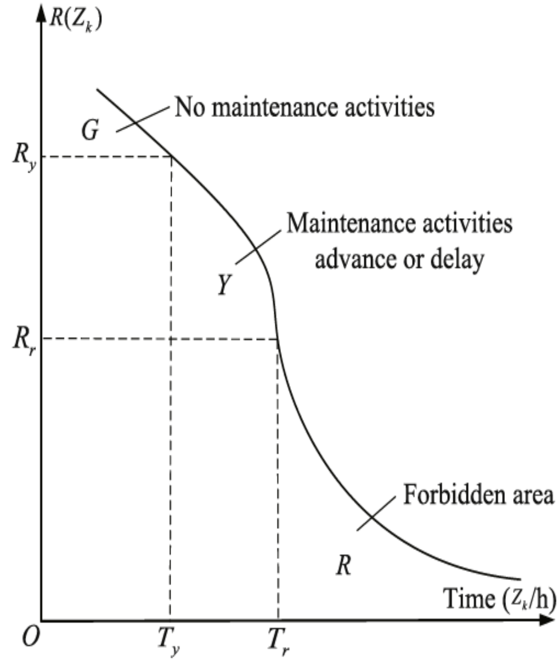

Figure 2.Time-based maintenance policy

If R <Rr, this is prohibited. In this case, for calculation purposes, the maintenance time (before Oi, j) is an infinite value a0 and the effective age of the machine is zero (i.e., Zky = 0). Therefore, the reliability value determines the duration of maintenance. In other words, the higher the failure frequency, the more serious the damage to the machine, so the longer the maintenance time. If the reliability value before processing Oi, j (called Rb) is in the G region, the maintenance time before processing Oi, j, which is a linear function of the age difference, is shorter than the initial maintenance time ak (which can occur in scenario 2 when RbRy and (Rk(t')) are in region Y or occurs in scenario 3, while RbRy and R Rr). If the reliability value (Rk(t')) is in the Y region, the time, which is a quadratic function of the age difference, is greater than ak (which can occur in scenario 2 and Rb<Ry or deferred maintenance, or in scenario 3). Accordingly, the actual time for the y-th maintenance is calculated as:

(3)

$$MT_k(y) = \begin{cases} a_k - b\left(T_y - Z_k\right) & 0 \le Z_k \le T_y \\ a_k + b\left(T_y - Z_k\right)^2 & T_y < Z_k \le T_r \\ a_0 & R' < R_r \end{cases}$$

whereak is the original maintenance time of Mk and b is the ratio coefficient. Ty and Tr are the reliability ages corresponding to Ry and Rr, respectively. In addition, Zk is the effective age at which accurate maintenance is performed. (3) (2) Integrated Multi-Objective Optimization Model for Production and Accurate Maintenance Scheduling In this section, we present the assumptions of the mathematical model and the corresponding symbols. Then, an integrated multi-objective optimization model is created by combining production planning with AM.

Assumptions and Symbols The integrated multi-objective optimization model considered in this paper is based on the following assumptions:

(1) All jobs have the same priority and the processing time of each operation is predetermined.

(2) Once a repair operation starts, it must be completed without interruption.

(3) At a given time, each machine can only process one operation. Meanwhile, an operation can only be processed by one machine in the optional machine set Mopt.

(4) The effective age of the machine is determined by the processing/working time considering the impact of other factors (e.g., idle time).

(5) After incomplete maintenance of the machine, its effective age can return to the assumed state Zky. Therefore, the notations used in the mathematical model are summarized as follows:

2-4- Model Components

The model components are as follows:

- n: Total number of jobs.
- m: Total number of machines.
- ni: Total number of operations for job Ji.
- uk: Total maintenance time for machine Mk.
- Zk: Effective age/performance of machine Mk.
- g: Total number of objectives.
- Ci,j: Completion time of operation Oi,j.
- Ai: Arrival time of job Ji.
- Oi,j: j-th operation of job Ji.
- sptijk: Start processing time of Oi,j on machine Mk.
- pij: Repair time of Oi,j on machine Mk.
- eptijk: End processing time of Oi,j on machine Mk.
- sitk: Start idle time of machine Mk.
- satijk: Start setup time of Oi,j on machine Mk.
- eatijk: End setup time of Oi,j on machine Mk.
- wk: Maintenance cost per unit time for machine Mk.
- ck: Setup cost per unit time for machine Mk.
- MTk: Array of maintenance times for machine Mk.

Decision Variables

xijk: 0-1 variable, whether Oi,j is processed on Mk.

4-4- Functions and Constraints

The multi-objective optimization model has two objective functions. The first objective function, f1, represents the repair and setup time of the damaged machine, and the second objective function, f2, represents the repair and setup cost of the system. Therefore, by minimizing these two functions, the time and cost of repair and maintenance can be reduced, which in turn will reduce production costs. By reducing repair and maintenance costs and time, machines return to production lines faster. These functions are:

$$(4)\ \min\{f_1, f_2\}$$

$$(5)\ f_1 = \sum_{i=1}^{n}\sum_{j=1}^{n_i}\sum_{k=1}^{m}\left(at_{ijk}.x_{ijk}\right)$$

$$(6)\ f_2 = \sum_{k=1}^{m}\sum_{y=1}^{u_k}\left(w_k MT_k(y)\right) + \sum_{i=1}^{n}\sum_{j=1}^{n_i}\sum_{k=1}^{m}\left(c_k.p_{ijk}.x_{ijk}\right)$$

$$(7)\ \begin{array}{l} spt_{i(j-1)} + x_{i(j-1)}.p_{i(j-1)k'} \le sat_{ijk}, \\ \forall i \in J', \forall\{j, j-1\} \subseteq I_i,\ \forall\{k,k'\} \subseteq M' \end{array}$$

$$(8)\ \begin{array}{l} spt_{i(j-1)} + x_{i(j-1)}.p_{i(j-1)k'} \le sat_{ijk}, \\ \forall i \in J', \forall\{j, j-1\} \subseteq I_i,\ \forall\{k,k'\} \subseteq M' \end{array}$$

$$(9)\ \begin{array}{l} spt_{ijk} + x_{ijk}.p_{ijk} \le ept_{ijk}, \\ \forall i \in J', \forall j \in I_i,\ \forall k \in M' \end{array}$$

$$(10)\ \begin{array}{l} sat_{ijk} \ge \max\left\{sit_k, ept_{i(j-1)k'}\right\}, \\ \forall i \in J', \forall\{j, j-1\} \subseteq I_i,\ \forall\{k,k'\} \subseteq M' \end{array}$$

$$(11)\ sit_k = \begin{cases} ept_{i'j'k} + MT_k(y), & maintenance\ beore\ O_{i,j} \\ ept_{i'j'k} & O.w \end{cases},\ \forall i \in J', \forall j \in I_i,\ \forall k \in M'$$

$$(12)\ sat_{i,j,k} + at_{i,j,k} \le eat_{i,j,k},\quad \forall i \in J', \forall j \in I_i,\ \forall k \in M'$$

$$(13)\ eat_{i,j,k} \le spt_{i,j,k},\quad \forall i \in J', \forall j \in I_i,\ \forall k \in M'$$

$$(14)\ 0 < R_r \le R_k(Z_k)$$

$$(15)\ \sum_{k=1}^{m} x_{i,j,k} = 1,\quad \forall i \in J', \forall j \in I_i$$

$$(16)\ \sum_{i=1}^{n}\sum_{j=1}^{n_i} x_{i,j,k} = 1,\quad \forall k \in M'$$

$$(17)\ x_{i,j,k} = \begin{cases} 1, & O_{i.j}\ is\ processed\ on\ M_k \\ 0, & O.W \end{cases},\ \forall i \in J', \forall j \in I_i,\ \forall k \in M'$$

$$(18)\ \mathrm{C_{i,j}} \ge 0,\ \mathrm{A_i} \ge 0,\quad \forall i \in J', \forall j \in I_i$$

$$(19)\ \mathrm{c_k} \ge 0,\ \mathrm{w_k} \ge 0,\ \mathrm{u_k} \ge 0,\ \mathrm{s_{itk}} \ge 0,\quad \forall k \in M'$$

Constraint (7) is the operation precedence constraint, which means that an operation must start setting up after the completion of the previous operation. Constraint (8) states that the start processing time of Oi,j must be less than its end processing time. Constraint (9) indicates that the start setup time of Oi,j must be greater than or equal to the time when the machine starts working and the end processing time of the previous job on the same machine. Constraint (10) determines the start idle time of the machine (Oi,j is an immediate previous activity of Oi,j on machine Mk). Constraint (11) specifies the setup time constraint for Oi,j. Constraint (12) defines the relationship between the final setup time and the start processing time of Oi,j. Constraint (13) states that the reliability Rk(Zk) should not be less than the red zone reliability threshold Rr. Constraint (14) ensures that each operation can only be assigned to one of the available/suitable machines. Constraint (15) enforces that a machine can only process one operation at a time. Constraint (16) indicates that xijk is a binary variable. Constraints (17)-(19) are non-negativity constraints.

Inventory Management

There can be a dependency between the different goods in stock and those used by the organization, so the policies adopted for one good will usually affect the other goods in stock. In this section, a new optimization function is introduced that aims to reduce the cost of storing parts in the warehouse. This cost is the same as the inventory holding cost, which includes the cost involved in inventory, taxes, insurance, and the like.

The cost of placing an order from a supplier for a number of different products consists of the following two components:

- **Total order cost:** This is independent of the number of different products in a single order.
- **Partial order cost:** This depends on the number of different products in an order.

Due to the existence of a total order cost, the use of group ordering can lead to significant cost savings. This saving is particularly significant when the demand between items is closely related.

As in the previous section, to develop the inventory model, assumptions must be considered and the model developed on the basis of these assumptions. The assumptions are as follows:

- **Existence of deterministic and uniform demand.**
- **Linearity of holding cost.**
- **Shortage is not allowed.**
- **Warehouse space constraint.**

It can be seen that in the above assumptions, in order to make the model more practical, the warehouse space constraint, which most existing inventory control systems face in practice, has also been added to the model. Therefore, the optimization function is defined as follows:

$$(20)\quad f_4 = \frac{\sum_{j=1}^{n}\left(k_j D_j h_j\right)}{2} T + \frac{S + \sum_{j=1}^{n} \frac{s_j}{k_j}}{T}$$

$$(21)\quad f_5 = T \sum_{j=1}^{n}\left(c_j k_j D_j\right)$$

where function f4 represents the total ordering and inventory holding cost per unit time, and objective function f5 is the total capital cost tied up in inventory. The constraint of the optimization problem is as follows:

$$(22)\ \sum_{j=1}^{n} k_j D_j v_j \leq \frac{V}{T}$$

where we have in the above relationships:

- **n:** Number of products.
- **i:** Product index n, ..., i = 1.
- **Di:** Annual demand for product i.
- **hi:** Annual holding cost for product i.
- **S:** Total order cost per order.
- **si:** Partial order cost that is paid if product i is ordered.
- **ci:** Cost of purchasing one unit of product i.
- **V:** Maximum warehouse space.
- **vi:** Space required to store one unit of product i.

The decision variables also include **T**, the time between two consecutive orders, and **ki**, the integer order quantity for product i. The optimization algorithm should reduce the inventory cost by selecting the optimal values of these two parameters.

Numerical Example

In addition to the MPSO method, the NSGA-III optimization method is also used for optimization. Therefore, this method will be explained first. It should be noted that the simulations were performed in the MATLAB 2014a software environment and on a Core i5 laptop with a 2.33 GHz processor and 4 GB RAM.

In order to simulate the algorithms, data were selected from the article by XiaohuiX[1] and colleagues (11). It is assumed that the number of machines and tasks is 4. In other words, there are four machines in the production line, each of which performs one task. Tables (1) to (3) show the simulation parameters:

TABLE 1: SIMULATION PARAMETERS: TIME PER JOB

J_1	O	M_1	M_2	M_3	M_4	J	M_1	M_2	M_3	M_4
	$O_{1,1}$	-	8	12	13	J_3	-	6	9	15
	$O_{1,2}$	16	-	15	7		5	2	-	14
	$O_{1,3}$	15	16	3	6		6	6	-	12
	$O_{1,4}$	8	15	-	8		14	-	4	13
J_2	$O_{4,1}$	13	20	15	5	J_4	14	8	9	11
	$O_{4,2}$	18	20	3	15		10	2	5	4
	$O_{4,3}$	13	8	6	15		18	11	16	8
	$O_{4,4}$	5	2	10	15		3	7	12	12

TABLE 2: SIMULATION PARAMETERS: COST PER MACHINE

M	J	J_1	J_2	J_3	J_4	M	J	J_1	J_2	J_3	J_4
M_1	J_1	1	2	1	3	M_3	J_1	1	2	1	3
	J_2	1	1	3	2		J_2	2	1	3	2
	J_3	1	1	1	2		J_3	1	1	1	1
	J_4	3	1	1	1		J_4	3	1	1	1
M_2	J_1	1	2	1	3	M_4	J_1	1	2	1	3
	J_2	1	1	3	2		J_2	1	1	1	3
	J_3	2	1	1	1		J_3	2	1	1	1
	J_4	3	2	2	1		J_4	2	2	2	3

TABLE 3: SIMULATION PARAMETERS

Parameter	M_1	M_2	M_3	M_4
β_k	1.6	1.7	1.6	1.8
η_k	78	75	73	77
a_k	4	3	2	3
p_k	0.65	0.63	0.7	0.75
w_k	18	20	19	17
c_k	8	5	10	9

To evaluate the performance of the algorithm, the results were simulated in three scenarios, the details of which will be explained below. Table (4) also shows the simulation parameters.

TABLE 4: MPSO ALGORITHM PARAMETERS

Parameter	Value
Number of variables	4
Maximum problem iterations	100
Number of objective functions	3
Particle swarm population	200
Number of archives	100
Particle inertia coefficient	0.5
Particle inertia damping coefficient	0.99
Local learning coefficient	1.5
Global learning coefficient	1.5
Growth rate	0.1

In multi-objective problems, there are usually multiple optimal solutions, each of which optimizes one of the functions. This is called the selection of dominant solutions. In the present study, the solution that minimizes the repair time was considered as the optimal solution. The faster a machine returns to the production line, the more efficient the company becomes and as a result can produce more products.

The differences in the optimization problem and the optimization algorithm, which used NSGA-II instead of MPSO, which is an improved version of the genetic optimization algorithm.

Figures (3) to (5) show the output of the simulations. Figure (3) shows the output of the repair time of the machines for four machines. It can be seen that except for machine number 3, the proposed method is better than the reference method (11) for the other machines. This figure shows that for machine number 2, the reference method is slightly better than the proposed method. However, this figure shows that the proposed algorithm has been more efficient for machines number 1 and 4.

Figure (4) also shows the output of the two algorithms for the cost of the machines. It can be seen that for all four machines, the proposed method is more efficient and as a result the repair cost is reduced. This is because the Weibull function is used to model the failure of mechanical parts. A new function is considered in the problem that is related to the number of failures, which is indirectly related to the repair and maintenance cost.

Figure (5) also shows the output of the two algorithms for the third objective function. This figure shows that the performance of the proposed algorithm is much better for all four machines, and the probability that the machine will fail less in its lifetime is higher. Therefore, this figure clearly shows that using a new objective function can improve the performance of the problem.

In the second scenario, it was assumed that the number of machines and tasks is three. In other words, the fourth task and machine were removed. The obtained results are shown in Figures (6) to (8). Figure (6) shows the output of the repair time of the machines for three machines. It can be seen that unlike the previous scenario, the performance of the proposed method is better than the reference method for all machines. Figure (7) also shows the output of the two algorithms for the cost of the machines.

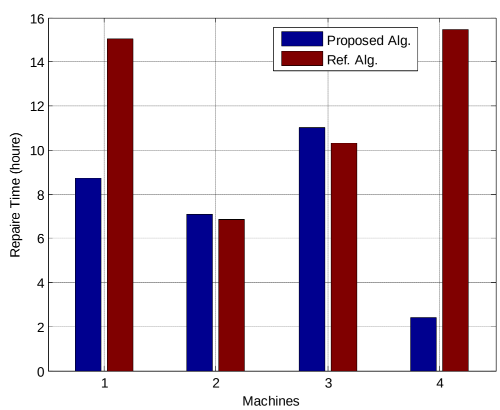

Figure 3.Repair time of devices in Scenario 1

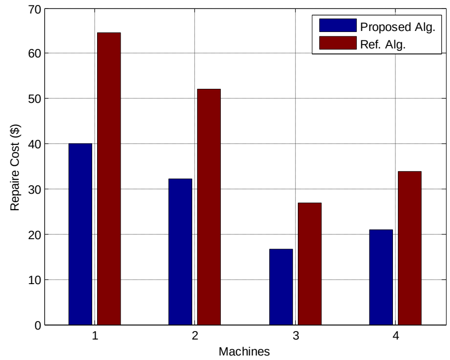

Figure 4. Repair and maintenance costs of devices in Scenario 1

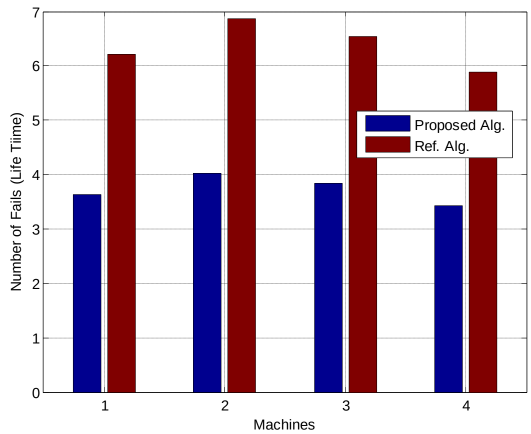

Figure 5. Average number of failures during the useful life of the device Scenario 1

It can be seen that for all three machines, the proposed method is more efficient than the method proposed in the reference paper, and as a result the repair cost is reduced. Figure (8) also shows the output of the two algorithms for the third objective function. This figure also shows that the performance of the proposed algorithm is much better for all three machines, and the probability that the machine will fail less in its lifetime is higher.

In the third scenario, the number of machines was considered to be four, as in the first scenario. However, this scenario has one difference from the first scenario. This change is the change of formula 3, which is used in a single sentence and it is assumed that maintenance is independent of the life of the machine. The effect of precise maintenance has not been considered.

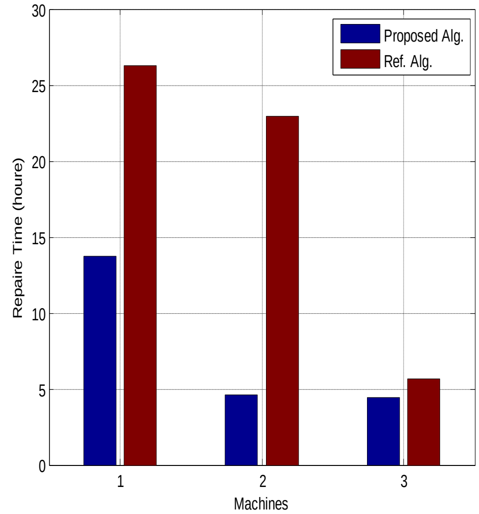

Figure 6. Repair time of devices in Scenario 2

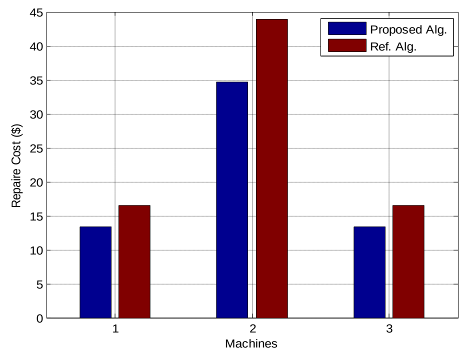

Figure 7. Repair and maintenance costs of devices in Scenario 2

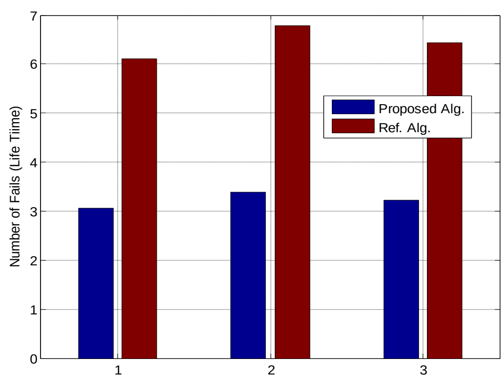

Figure 8. Average number of failures during the useful life of the device Scenario 2

The results are shown in Figures (9) to (11). It can be seen that in all three figures, the performance of the proposed method is better than the reference method. In addition, these figures clearly show that precise maintenance reduces the cost and repair time, although this does not have a significant impact on the number of failures during the life of the machine.

Figure (9) shows the output of the repair time of the machines for four machines. It can be seen that unlike the previous scenario, the performance of the proposed method is better than the reference method for all machines. Figure (10) also shows the output of the two algorithms for the cost of the machines. It can be seen that, as in the previous scenario, the proposed method is more efficient than the method proposed in the reference paper for all four machines, and as a result the repair cost is reduced. The reason for this has been explained before. Figure (11) also shows the output of the two algorithms for the third objective function. This figure also shows that the performance of the proposed algorithm is much better for all four machines, and the probability that the machine will fail less in its lifetime is higher.

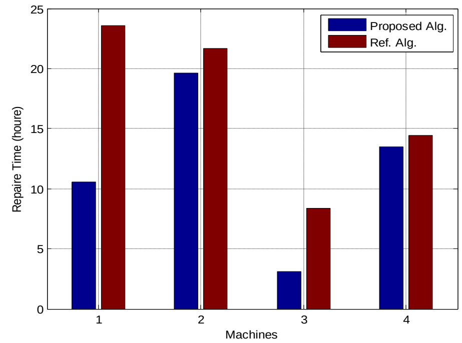

Figure 9. Repair time of devices in Scenario 3

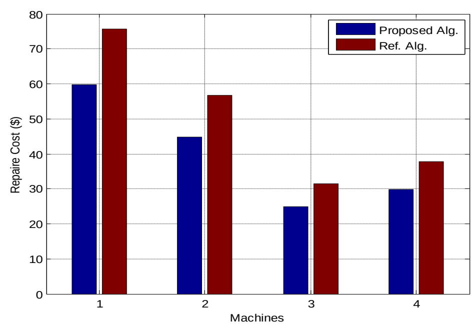

Figure 10. Repair and maintenance costs of devices in Scenario 3

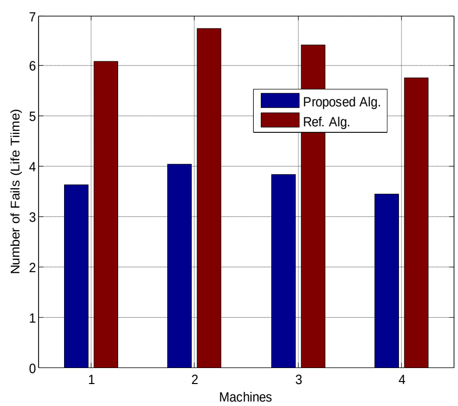

Figure 11. Average number of failures during the useful life of the device Scenario 3

In order to evaluate more accurately, we will investigate the changes of different parameters. This investigation is only performed on our proposed method because the parameters and objective functions are selected based on the proposed method. For this purpose, we investigated the changes of different parameters and measured their effect on the values of the objective functions. Simultaneous changes of two parameters were considered. We assumed that the time values in Table (1) are increasing and the output value is calculated for each unit increase. This table shows the time. It should be noted that for the values not defined in this table, this unit increase has not been applied. The second variable considered was the change in the number of tasks, which is shown in Table (2). Therefore, we calculated the results as three-dimensional functions and plotted them.

Figure (12) shows the obtained values for the repair and maintenance time objective function for each of the four assumed machines. It can be seen that for each machine, the value of the objective function, i.e., the repair and maintenance time, changes, and this is more for machine 3 than for the other machines. It can be concluded from these figures that the assumed time and also the number of tasks can have an impact on the performance of the systems. As a result, it can also increase the repair and maintenance time. In addition, this figure shows that the performance of the systems may vary between different machines.

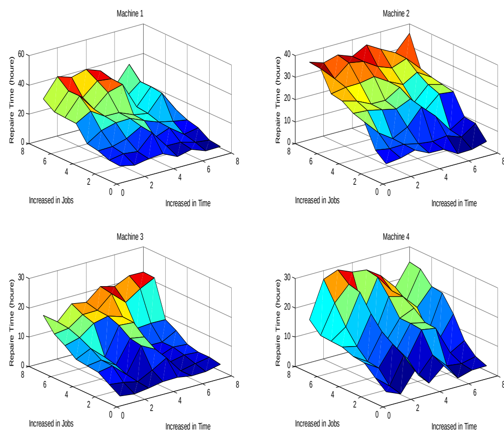

Figure 12. Effect of different parameters on the first objective function

Figure (13) also shows the performance of each of the four machines based on the second objective function, i.e., the repair cost. This figure also clearly shows that the effect of changes in task execution time and the number of tasks is different for different machines. In other words, it can be seen from this figure that for each of the four machines, the cost will also change with the increase of the input variables. As a result, it is not possible to consider the same scenarios for all machines, and each machine must be considered according to its own assumptions. In addition, this figure also shows that the repair and maintenance cost is higher for machines 1 and 2 than for the other two machines.

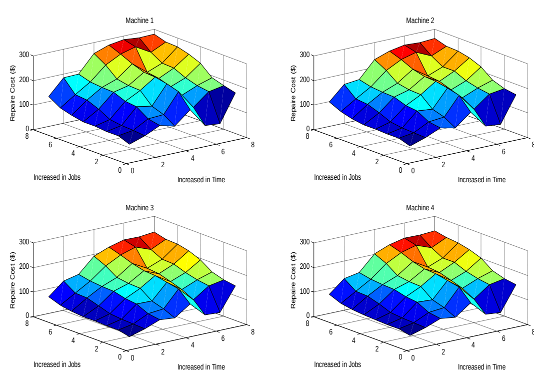

Figure 13. Effect of different parameters on the second objective function

Figure (14) also shows the performance of each of the four machines based on the third objective function, i.e., the number of failures in the machine's lifetime. As in the previous two figures, it can be seen that for different machines, the effect of changes in task execution time and the number of tasks on the useful life of the machine is different. In other words, it can be seen from this figure that for each of the four machines, with the increase of the input variables, the number of times the machine fails will also change.

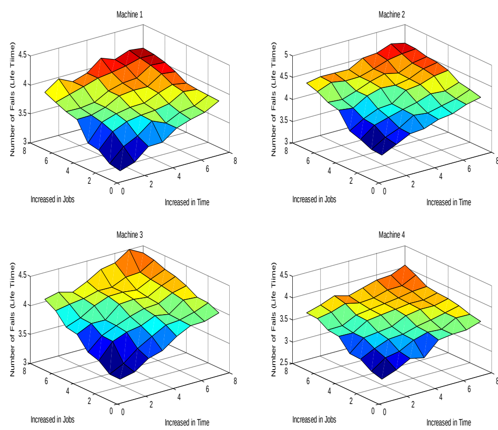

Figure 14. Effect of different parameters on the third objective function

Inventory optimization problem

As mentioned, the simulation values in the present study are shown in Table (5). The algorithm values are the same as the previous problem because the investigations showed that the problem can also be optimized using these values. In these simulations, it is assumed that the order is placed in two stages and a total of 4 products are to be purchased. For simplicity, the cost is also considered as one unit, which can be different. In fact, since the product is selected based on need and not cost, the cost has no effect on the algorithm process. It is also assumed in this simulation that there is only one warehouse for storage, which is a valid assumption for many organizations and departments.

Values	Parameter
100,250	Demand
5,10,15,20	Total ordering cost
[0. 5,5]	Partial ordering cost
10,20,30,50	Number of products
[0. 2,3]	Holding cost
1	Storage space required for each item
1	Purchase price of each item

Figure (15) shows the output of the inventory valuation function. It can be seen in this function that the larger the range of acceptable optimal production, the smoother the objective function, and as a result, production planning can be better because the capacity of the company's different warehouses has more flexibility.

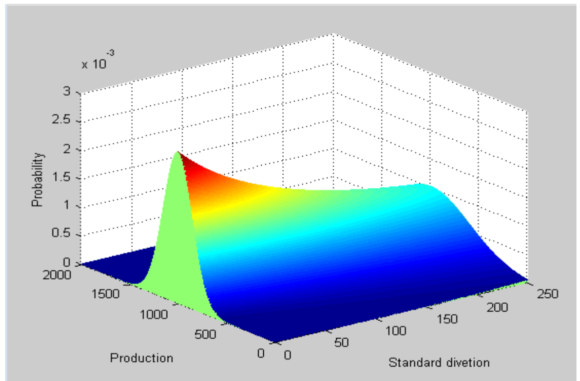

Figure 15. Output of the inventory valuation function

Figures (16) and (17) respectively show the set of dominant solutions for each of the two algorithms under consideration. By examining these two figures, it can be seen that the dispersion of solutions in the MPSO algorithm is less than that of the NSGAII algorithm, which is one of the advantages of the MPSO algorithm. Because in a multi-objective optimization problem, the less the dispersion of solutions, the better the performance of the algorithm will be. These two figures show that the values obtained for the variables based on the MPSO algorithm are less than those of the other algorithm, and therefore both the order time and the number of orders have been reduced. In both figures, the first function refers to the order quantity and the second function refers to the time between two consecutive orders.

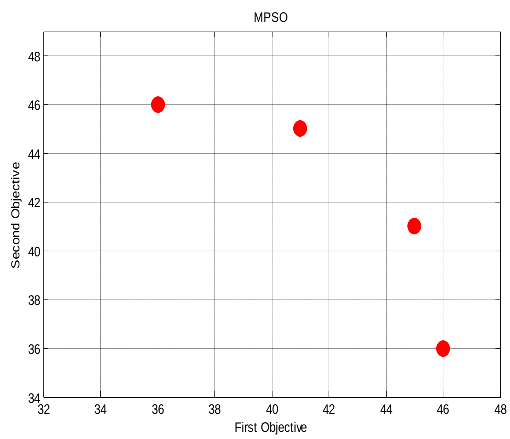

Figure 16. Pareto optimal solution for the MPSO algorithm

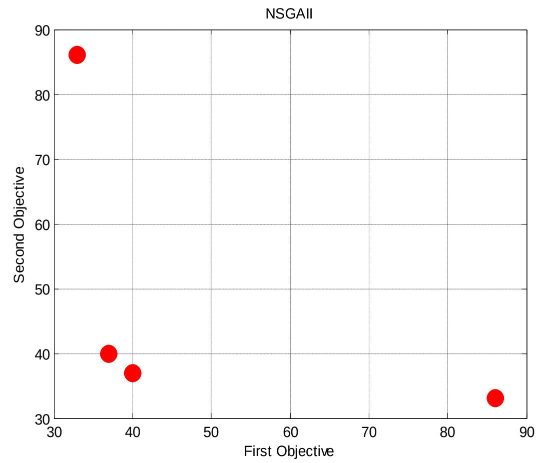

Figure 17. Pareto optimal solution for the NSGAII algorithm

By substituting these variables, the set of solutions for the two objective functions is also obtained. The results obtained for the first objective function are shown in Figure (18) and the results obtained for the second objective function are shown in Figure (19). The meaning of the first and second objective functions is fully explained in Chapter 3. Therefore, by examining these two figures, it can be concluded that for some Pareto solutions, the performance of the NSGAII algorithm is better than MPSO, and for others, the performance of MPSO is higher than NSGAII. Therefore, this figure clearly shows that both algorithms can have acceptable performance. However, as can be seen in these two figures, the dispersion of solutions in the MPSO algorithm is less; therefore, it can be concluded that the overall performance of the MPSO algorithm is better than the NSGAII algorithm.

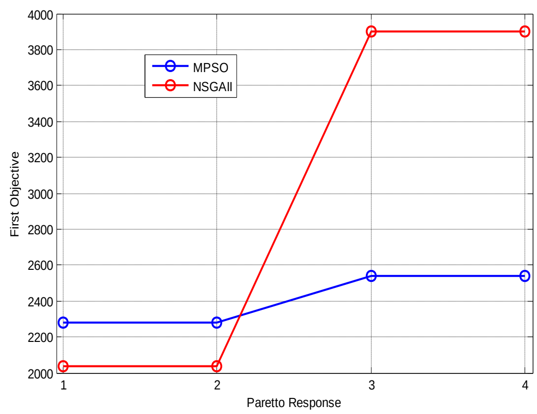

Figure 18. Optimal solution for the first objective function

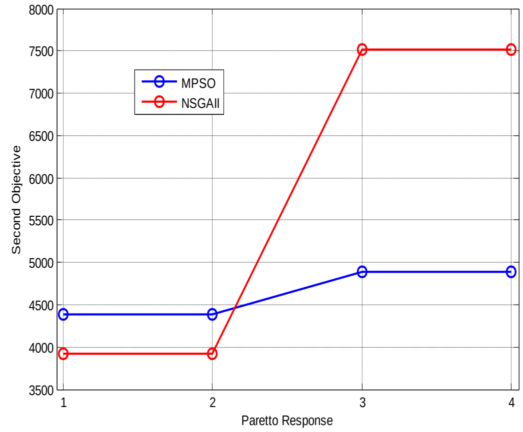

Figure 19. Optimal solution for the second objective function

6. CONCLUSION

While the use of the Gaussian model can provide us with a deep and acceptable insight, it is necessary to optimize the use of effective parameters in warehousing such as time, number of orders and optimization algorithm to optimize the use of the warehouse. As mentioned before, there may be a dependency between the different goods in the warehouse and used by the organization. Hence, the policies adopted for one good will affect the other goods in the warehouse. In this study, a new optimization function was introduced, which aims to reduce the cost of keeping parts in stock. This cost is the same as the inventory holding cost, which includes the cost involved in inventory.

Based on the review conducted in this study, it is suggested that machine learning algorithms be used for the aforementioned problem in future research. Therefore, artificial neural networks can also be used as a suitable solution.

REFERENCES

[1] Hosseini, M. H. (2020). Modeling and solving a bi-objective integrated production planning and maintenance problem with the aim of reducing customer dissatisfaction. Journal of Industrial Management Studies, 18(56).

[2] SajjadiNezhad, A., &Lotfi, M. (2019). A model for optimizing preventive maintenance scheduling for multi-component systems using a genetic algorithm. Journal of Industrial Management Studies, 17(55).

[3] Gholamrezaei, M., &KhadamiZare, H. (2015). Developing a multi-product, multi-period, multi-objective production planning model with fuzzy parameters. Production and Operations Management, 6(1).

[4] AhmadiNejadfarsi, N. (2018). Applied model of linear programming to minimize production costs in the Adrang furniture workshop. The 1st National Conference on New Studies and Research in Environmental and Management Sciences.

[5] Yang L, Zhao Y, Peng R, Ma XB.(2018) Hybrid preventive maintenance of competing failures under random environment. ReliabEngSyst Saf;174:130–40.

[6] Poppe J, Boute RN, Lambrecht MR.(2018) A hybrid condition-based maintenance policy for continuously monitored components with two degradation thresholds. Eur J Oper Res

[7] Martinod RM, Olivier B, Castaneda LF, Rezg N.(2018). Maintenance policy optimisation for multi-component systems considering degradation of components and imperfect maintenance actions. ComputInd Eng;124:100–12

[8] Yang L, Ye ZS, Lee CG, Yang SF, Peng R.(2019) A two-phase preventive maintenance policy considering imperfect repair and postponed replacement. Eur J Oper Res. 274:966–77.

[9] Rifai AP, Nguyen HT, Aoyama H, Dawal SZM, Masruroh NA.(2018). Non-dominated sorting biogeography-based optimization for bi-objective reentrant flexible manufacturing system scheduling. Appl Soft Comput;62:187–202

[10] Yu T, Zhu C, Chang Q, Wang JF.(2019) Imperfect corrective maintenance scheduling for energy efficient manufacturing systems through online task allocation method. J ManufSyst 2019;53:282–90.

[11] Xiaohui C, Youjun A, Zhiyao Z, Yinghei,(2020) An approximate nondominated sorting genetic algorithm to integrate optimization of production scheduling and accurate maintenance based on reliability intervals, Journal of Manufacturing Systems 54; 227-241