INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 20, Issue: 4, Month: August, Year: 2025
Article Number: 6888, https://doi.org/10.15837/ijccc.2025.4.6888

CCC Publications

Implementation of the Maintenance and Repair System Using the Ant Colony Algorithm

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Abstract

In this research, the issue of maintenance and repairs for machines is addressed by considering the skills of the maintenance and repair team, as well as the varying repair times for different machines and devices. The goal is to achieve a balanced workload for repairmen based on their skills and experience. In order to investigate the efficiency of the proposed algorithms, two sets including small dimensions with 8 problems and medium to large dimensions with 12 problems have been produced. Also, in this research two approaches have been utilized to tackle this problem. The first is a mixed integer programming model for small dimensions, but its limitations in solving medium to larger problems make the use of meta-heuristic algorithms necessary, utilizes an ant colony optimization (ACO) algorithm to solve the model for practical scales. Also, in order to compare which algorithm has a better efficiency for evaluation, the ACO and GA algorithm have been used. Computational results have demonstrated the superiority of the ant algorithm over other heuristic algorithms in solving real-sized problems. This approach has been successfully implemented in the repair and maintenance department of Khosroniko Plast Production Company.

Keywords: Genetic Algorithm (GA), Mixed Integer Programming (MIP), MATLAB, Maintenance and repairs problem, Repair and maintenance team, preventive maintenance (PM), Ant colony optimization (ACO)

1 Introduction

The economic performance of production units depends on the reliability, productivity of machines, equipment and production system. Due to the expansion and application of technology and the complexity of modern systems in organizations and the competitiveness of conditions, maintenance strategies must be strong in such conditions. An effective and efficient maintenance depends entirely on the strategy employed. In general, maintenance is defined as the combination of all technical and administrative actions, including monitoring that ensure a system is in its required performance state [1],[2],[3]. Maintenance and repairs of a system are usually related to maintenance and repairs of that system, such as repair, replacement, overhaul, inspection, service, adjustment, testing, measuring, and fault diagnosis in order to prevent any failure that leads to interruption in operations [4],[5],[6]. Maintenance is a set of activities that are performed in a system to maintain it in an acceptable working condition.[7],[8],[9].

Maintenance and repairs of a system usually involves the evaluation of maintenance and repair strategies, including identifying the most appropriate maintenance and repair strategies for different machines by maximizing benefits through considering sets of constraints. However, the benefits of an effective maintenance strategy outweigh its monetary value, as issues such as employee safety, environmental impact, and production performance are significantly affected by an effective maintenance program. Despite this, several maintenance strategies are used in different organizations, such as corrective maintenance (CM), preventive maintenance (PM), total productive maintenance (TPM), breakdown maintenance (BM), condition-based maintenance (CBM) and time-based maintenance (TBM[10],[11].The implementation of maintenance and repairs depends on maintenance and repair policies, which can be defined as a plan that is used to provide and direct instructions to perform more maintenance actions required by a system [12],[3],[13].System maintenance and repairs can improve system reliability and prevent possible failures and their consequences) [14]. The implementation of maintenance and repairs is like a new project and work, and it is not possible to start a new work and it will naturally be faced with challenges. However, with the proper implementation of maintenance and repairs in industries, it is possible to increase the efficiency and effectiveness of equipment in production lines, reduce the cost of remedial repairs, and also reduce the cost of staff in the maintenance and repair department. Re-maintenance of the equipment is not done by the repair and maintenance unit. The benefits of optimal implementation of maintenance and repairs can be increased production efficiency, reduction of equipment stoppages in production lines, reduction of corrective repairs, reduction of depreciation of equipment during correction and re-repairs, and ultimately reduces the re-planning of the maintenance and repairs unit by managers and the planners of the maintenance and repair unit also increases production and aligns plans with the production planning unit.

Structure of the paper is as follows; in section two literature review of the study presented. Section three describes the methodology of the research, specifically ant colony algorithm. Finally, data analysis and conclusions are discussed in sections four and five respectively.

2 Review of research literature

2.1 Maintenance

Maintenance is a set of actions aimed at maintaining or restoring an item to a condition in which it can perform a required function. Maintenance can be executed on an equipment following a failure (reactive maintenance) or on a preliminary basis to prevent failure (proactive maintenance) [15],[16].

Measuring the performance of maintenance and repair systems can be based on various factors [17]. Whenever PM is implemented, the life of the production system is significantly increased and unwanted downtime is prevented [5].

2.2 Maintenance and repair policies

Today, the efficiency and effectiveness of an entire production operation depends on the stable performance of systems or equipment, which can lead to valuable improvements in terms of quality, cost, and time [18], [19].[20]. In order to produce better product quality at minimum cost, the availability and reliability of the production line that popularly known as the system, plays a major role in maintaining a competitive advantage over other manufacturing organizations [21], [22]. Therefore, systems are considered an inevitable part of production that require constant attention and maintenance to achieve optimal operating conditions [23],[5]. Since PM is one of the maintenance and repair policies, it is related to maintenance and repair planning, which requires a long-term strategy to implement maintenance and repair actions in a predetermined period of time. The scope of PM planning includes all aspects of PM that must be integrated with appropriate planning in order to aid decision-making in cases where action should be taken to improve system performance through monitoring. PM planning is also one of the visions of management that requires considering the goals, planning and methods before implementing PM in a system [24],[5].

2.3 Planning for maintenance and repairs

In the field of maintenance and repairs, planning includes activities that are determined and prepared with the help of all maintenance and repair resources such as material requirements, labor requirements, time determination and technical references related to equipment, before the implementation of a task [25]. The issue of maintenance planning and scheduling, similar to many other planning dilemmas, revolves around the optimization of developing effective maintenance strategies and appropriately distributing maintenance resources and responsibilities within the geospatial context [16].

2.4 Maintenance and repair strategies

System maintenance and repairs can improve the reliability of the system and avoid possible failures and their consequences [26]. Maintenance and repairs encompass a range of tasks aimed at prolonging the lifespan of machinery, minimizing the need for spare parts, reducing energy consumption, and cutting costs, all while improving the operational efficiency of the equipment [27]. Considering the development and application of technology and complexity of modern systems in organizations, maintenance strategies are needed to create a competitive environment in the production system [10]. Evaluation of maintenance and repair strategies involves identifying the most appropriate maintenance strategy for different machines by maximizing benefits by considering sets of constraints. A suitable maintenance strategy not only improves the organization to compete with others, but also leads to maximum profit [27],[28],[29].

2.5 Scheduled maintenance

An organization's ability to effectively plan maintenance in an organized and efficient way determines the success of implementing TPM programs [30]. The purpose of planned maintenance and repairs is to create and maintain optimal equipment and process conditions. Planned maintenance includes maintenance methods and approaches such as PM, TBM, CBM and CM. Planned maintenance is usually related to disciplined process planning, and the task of maintenance tracking requires good information systems to collect data and adapt to the plan to solve problems, as an indicator of the health of the planned maintenance management system. A complete strategy on planned maintenance includes a comprehensive plan for 8 main activities: guiding and supporting independent maintenance activities - fixed planned maintenance like mean time between failures (MTBF), extending the life of equipment, knowing when to use from various maintenance and repairs tasks using predicted maintenance and repairs technology, lubrication management, setting up planned maintenance and repairs structure, spare parts management, reducing maintenance and repair cost activities, strengthening and upgrading maintenance and forecasting skills. Success in using tools for maintenance and long-term repairs [31].

2.6 Implementation of maintenance and repairs

Planning PM and repairs in production units is an important task and plays a major role in system operation and planning. The economic operation of a facility system requires the simultaneous solution of all aspects of the operation schedule. Facing the problem of complexity of the system, there are different time scales, order of uncertainties, and different dimensions of the problems [32]. The implementation of PM, classification of equipment and its importance, reorganization of spare parts stocks, and a combination of maintenance planning taking into account production needs, will bring significant achievements to the company where this work was developed. The implementation of PM usually brings strong benefits to companies, and whenever possible, maintenance should be converted into independent maintenance, as pointed out by [33],[34],[35]. Reliability of system operation and production cost in industries are strongly influenced by the definitive repair of production facilities. An optimized maintenance schedule can save millions of dollars and potentially postpone some capital expenditures for new products when inventory margins are tight, allowing critical maintenance work to be done which may not be done otherwise. Therefore, the scheduling of maintenance and repairs of the industrial facilities system is an important part of the overall operation planning problems [36]. In industrial maintenance, the main goal of any company or industry is to guarantee the triple “cost, quality and time”;, it is not the simplest thing as it seems, but it is one of the necessary maintenances.

2.7 Framework for implementing world class maintenance and repair system elements

Warehouse management system (WMS) implementation framework has been developed based on literature review, discussion with experts and domain knowledge about maintenance and repair systems. Defining the best practices consistent with the maintenance and repair process can be considered as the maintenance and repair practices that enable the organization to achieve a competitive advantage over its competitors and thus achieve a world-class position like any other function in a maintenance and repair organization also has various sub-functions such as spare parts management, inventory preparation and operational cooperation, etc. A complete list of elements and their associated actions is identified in the proposed framework for WMS implementation. These elements and functions are based on the existing TPM knowledge and the implementation of the best maintenance and repair practices in different organizations. Such information may help or encourage the organization to use these practices to improve maintenance efforts and overall production performance [37],[38].

2.8 Optimization problem

Calculating the optimal solutions for most of the optimization problems that are observed in many practical fields is quite difficult and difficult. In practice, “good”; solutions obtained from heuristic and meta-heuristic patterns are usually used. Meta-heuristics includes a set of approximate optimization techniques that have gained popularity mainly during the last two decades. These methods provide “acceptable”; solutions in reasonable time to complex and hard problems in the fields of engineering and science. Unlike exact optimization patterns, meta-heuristics do not guarantee the optimality of the obtained solutions. The meta-heuristic search method can be defined as “a high-level general methodology that can be used as a guiding strategy in the design of specific heuristics to solve specialized optimization problems” [41], [42].

2.9 Optimization methods

There are two general categories of methods for solving optimization problems, including exact and approximate methods. Exact methods obtain the optimal solution and guarantee optimal conditions. Approximate methods produce high-quality solutions in reasonable time, but are not guaranteed to find the global optimal solution. In the category of approximate methods, there are two subcategories of algorithms including approximate and innovative algorithms. Unlike heuristic algorithms, which usually seek good solutions in reasonable time, approximation algorithms provide provable bounds for execution time and solution quality. Heuristic patterns are generally divided into two families: special heuristic patterns and meta-heuristics. Specific meta-heuristics are designed to solve a specific problem. Unlike exact methods, meta-heuristics are applicable to problems with large sizes and provide satisfactory solutions in reasonable time. In these algorithms, there is no guarantee to find the global optimal solution or some of it. Their application and use in many problems show their efficiency and effectiveness to solve complex and big problems. Among the main characteristics of the optimization problems that the use of meta-initiative algorithm seems suitable for their solution, can include the following materials. A simple problem (P class) with very large samples or dimensions; A simple problem (P-class) with severe real-time constraints (need to be solved at the same moment); non-deterministic polynomial-time hardness (NP-hard) with moderate dimensions or input data structure of the problem; optimization problems with objective functions or time constraints are non-analytical models of optimization problems that cannot be solved by a comprehensive method [39].

- GA Algorithm method

GA represent a methodological approach for addressing various problem-solving scenarios. This approach is applicable to a diverse array of economic challenges, including but not limited to the optimization of stock portfolios, forecasting bankruptcy, and predicting stock market trends. [40] predicted the efficiency of different combinations of trading techniques. They used GA on S&P500 data between 1928 and 1995 to reveal trading methods. But this method did not have a good yield compared to the old methods. Although the simulated research was done to improve the previous research. [41] implemented a GA program to predict the value of stocks in the Japanese stock market. The GA optimization technique was used to optimize the maintenance cost due to availability and reliability constraints [42], [43]. [44] used the GA and indicated that the GA could be used successfully to find a good solution very quickly and more suited to major problems than a random search, and a branch- bound approach. Javanmard and [45] used GA to optimize the PM scheduling model to predict downtime, cost, and reliability over a predetermined time interval. [46],[47] used different shell connection to stress analysis of flanged joint bolts. Kumhar and Kumar [48] used different metaheuristic techniques such as GA, particle swarm, and evolution strategy to schedule maintenance planning for the power system and found that the GA had the most minimization cost compared to other metaheuristics.

2.10 Ant Algorithm method

Ant optimization algorithm was extracted from [49] in doctoral thesis and became famous as ant colony. The ACO algorithm is known as swarm intelligence (group intelligence) and it models the behavior of real ants. Ants are insects that can form groups (colonies). Ant optimization algorithms have been successfully applied to solve many complex combinatorial problems, such as traveling salesman problem, vehicle routing problem, graph coloring problem, quadratic assignment problem, network traffic optimization problem, task scheduling problem, etc. have taken. A key event in recognizing the promise of ant optimization was the winning of the 50,000 Euro Marie Curie Excellence Award by the inventor of the ant algorithm [50]. Such a population-centric approach makes it possible for the ACO algorithm to solve dynamic optimization problems. Pay quite efficiently. The behavior of ants in carrying food, overcoming obstacles, building anthills and other operational moments is almost optimal. The principles of ants' behavior have been challenged a hundred million years after they "colonized"; the earth. Ants are self-organizing creatures. Self-organization is the result of the interaction between four components: multiple renewal; by accident; positive feedback and negative feedback. Such a feature is at the core of the problem because this feature is exactly what makes insects quickly adapt

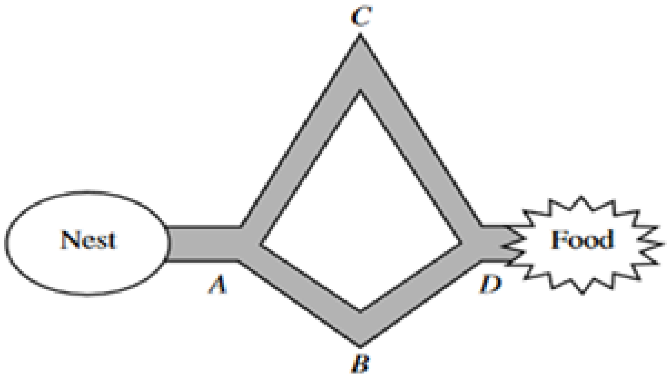

Figure 1: Asymmetric panel

to changing environmental conditions in order to achieve goals through low-level interactions. Since ants do not have eyes at all, their interactions are done through the chemical substance pheromone, which is used to mark the path. The more pheromones are placed on the path, the more the rest of the ants use this path; therefore, such a quantity shows that this route is one of the most optimal and shortest way. In an example of experiments with ants on an asymmetric bridge, we show how cooperative behavior of ants makes it possible to find the shortest path for food. The asymmetric bridge (Figure 1 connects the ant nest to the food source with two branches of different lengths. Experiments were conducted with a laboratory colony of Argentine ants (Irido-murmex humilis) that deposit pheromones in the nest and nest paths. The design of the experiments was as follows:

An asymmetrical panel taken from bridge A-B-C-D was built; the gate was opened at point A; the number of ants choosing the longer (A-C-D) and shorter bridge branches was counted. In the initial stages of the experiments, both branches were selected by the ants at the same speed. Almost all ants move along the shortest path A-B-D. At first, the branches did not have pheromone, so A-C-D and A-B-D branches were selected at equal rates. The ants that chose the shorter route A-B-D-B-A returned to the nest earlier with food and left pheromone trawl on this shorter branch. When forced to choose the next time, the ants preferred to move along the shorter branch of the bridge because the concentration of pheromones was higher on it. Therefore, pheromones accumulate faster on the A-B-D branch and attract ants to choose the shortest path [51].

3 Research method

In this research, out of 20 experimental problems in 2 dimensions, in small dimension including 8 problems and for medium to large dimension 12 problems are presented. Also, in this research, two approaches have been used to solve this problem. First, a mixed integer programming model is presented small dimension for the mentioned problem. But since the presented mathematical model is only able to solve problems with small dimensions, which makes the application of meta-heuristic algorithms inevitable. In the second approach for medium until large dimension, a meta-heuristic algorithm, namely ACO algorithm is presented in order to solve the model in practical scales. Also, in order to compare which algorithm has a better efficiency for evaluation, the ACO and GA algorithm have been used.

3.1 Conceptual model of research

Considering the review of the research background regarding the implementation of the maintenance and repair system with the method of ant algorithm in Khosrow Nikoplast industrial complex, it has been investigated to optimize and shorten the implementation of the maintenance and repair system.

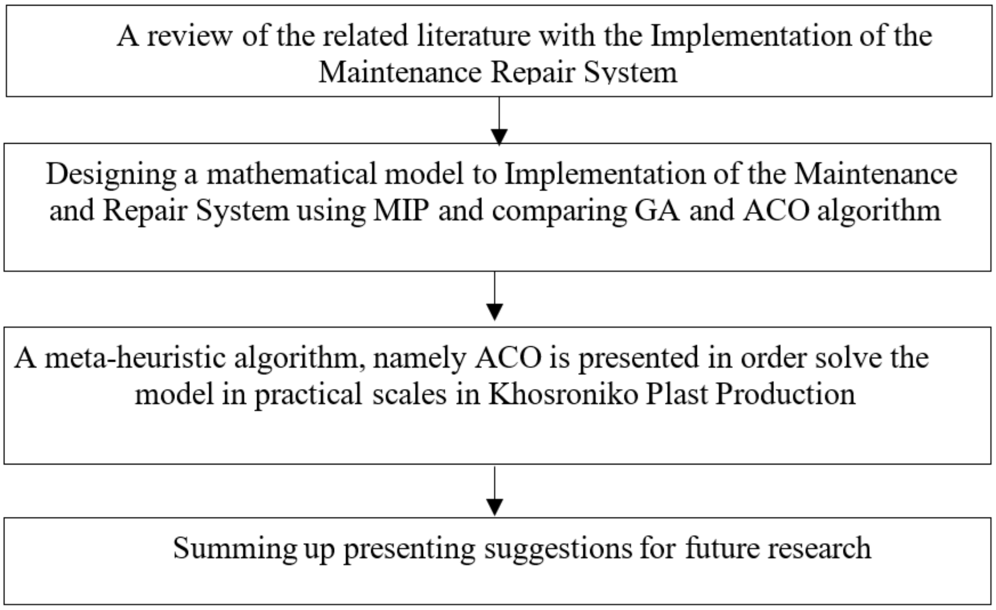

Figure 2: Conceptual model of research

4 Data analysis

4.1 Mixed Integer Programming (MIP)

MIP formulations provide a flexible and mathematically precise way of formulating many real-world problems. Specifically, integer programming is a commonly used technique for resource allocation and scheduling in wired and wireless networks. The two main problem types that MIP addresses are: (i) network synthesis and (ii) resource assignment problems. MIP optimization approaches facilitate also the introduction of a multi-objective function optimizing more than one goals under various offloading constraints (e.g., delay, energy and load balancing). Hence it can be often used as an optimization strategy during the task offloading problem. Usually, MIP provides a linear objective function, where at least one of the variables takes integer/binary values. However, they can often be used as benchmark approaches during the performance evaluation. MIP is one of the exact methods commonly used to find optimal solutions for small- and medium-sized problems, as well as lower and/or upper bounds in larger problems, and to benchmark the quality of the solutions and efficiency of the compared methods [52], [53], [54]. Moreover, unlike heuristics and meta-heuristics, the solution of MIP is the optimum with reasonable computational time for small- and medium-sized problems [55].

A Mixed-Integer Linear Program (MILP) is a special case of a Linear Program (LP) in which some of the decision variables are constrained to take only integer values. Given matrices A_1, A_2 and vectors f_1, f_2, b, the general MILP is given by:

$$\begin{gathered} min\ f_1^T x + f_2^T z \\ subject\ to\ A_1 x + A_2 z \leq b \\ z\ integer \end{gathered} \tag{1}$$

This problem is inherently non-convex: if for some problem $z_1 = 0$, $z_2 = 1$ are both solutions, points in between $z_1 \in (0, 1)$ violate the integer requirement on z_1 and are therefore infeasible. The problem is also in the class of NP complete problems [56], [57]. Many resource allocation problems are inherently discrete. For example, the manufacture of items commonly concerns only integer quantities of items. Also, the assignment of tasks to agents is discrete. Consider a simple task assignment problem in which N tasks are to be assigned to N agents. All the tasks must be assigned, and no agent can perform more than one task, hence every agent must be assigned a task. The tasks are discrete: they cannot be shared between agents. Consider a task assignment problem in which N

tasks are to be assigned to N agents. All the tasks must be assigned, and no agent can perform more than one task, hence every agent must be assigned a task. The tasks are discrete: they cannot be shared between agents. The assigning to wokes team maintenance agent i to task j is c_{ij}. To solve this problem for implementation of the preventive maintenance, define the decision variable $z_{ij} = 1$ if task i is assigned to agent j and 0 otherwise. Therefore, the problem can be written as:

$$\begin{aligned} min \ & \sum_{i=1}^{N}\sum_{j=1}^{N} c_{ij}z_{ij} \\ subject\ to \ & \sum_{i=1}^{N} z_{ij} = 1, \forall j \in \{1 \cdots N\} \\ & \sum_{j=1}^{N} z_{ij} = 1, \forall j \in \{1 \cdots N\} \\ & z_{ij} \in \{0,1\}, \forall i, j \end{aligned} \tag{2}$$

It turns out that the problem above is a special case and can be solved using only LP If the integer constraints $z_{ij} \in \{0, 1\}$ are replaced with simple bounds $0 \leq z_{ij} \leq 1$, then the vertices of the constraint set are all at integer values of z_{ij}, and since the LP solutions are at the vertices, these solutions will solve the integer problem too [58].

4.2 Genetic Algorithm

GAs is mainly driven from Darwin's theory. Regarding Darwin's theory, generations with superior traits and characteristics achieve higher survival and reproduction, and their superior traits and characteristics will be delivered to future generations. The response to a problem solved using GAs is permanently getting better. The GA commences with a series of responses that are proposed by chromosomes. Using such an algorithm, the answers gained from one population are used to produce the next population, along with a combination or mutation. During such a process, it is believed that the new population will be better than the preceding one. The choice of some chromosome responses from the total answers of the parents aiming at creating new responses for the children stems from their desirability, which is carried out using the fitting function. Naturally more proper responses have a better chance of reproducing. It lasts until a presupposed condition is observed (like the number of populations or the rate of improvement of the response) [59]. Totally, GAs is comprised of the following constituents. Many of inventions by human beings are inspired by the nature. GAs simulates the completion process in nature aiming at finding the best possible resolution for a problem probing through Candidate Solution Space. Within the process of the search for an optimal solution, first a set or a population of the primitive resolutions are produced. Then, through a consecutive set of generations a set of changed responses are produced (in each of GAs, certain changes are made on genes of the chromosomes of the population). The primitive responses usually change in a way that in every generation, the population of resolutions converge into an optimal response. This branch of Artificial Intelligence is based on the mechanism of living beings' evolution and the production of more successful and fit species inspired by nature. In other words, the major idea for GAs refers to Survival of the Fittest. A chromosome refers to a long and complicated string of Deoxyribonucleic Acid or DNA. The heredity factors identifying the personal characteristics or features of an individual form these chromosomes. Each of the characteristics of individuals is coded based on a combination of DNA in human genes. There are four bases in living beings' body to produce chromosomes using DNA as follows:

- Base A or Adenine;
- Base B or Cytosine;
- Base G or Guanine;

DRT	TTD	WFD	VRW	SM	SS	ER	MPS	RM	WPS
FM	PQM	LM	SPMS	SPM	RMC	SUMS	SPMT	ES	EI

Table 1: Scheduling process chromosomes

- Base T or Thymine.

As alphabet comprise the structure of a language, a meaningful combination of chromosomes (and its bases) produces specific manuals for cells. The changes in chromosomes occur during reproduction process. Parents' chromosomes are exchanged randomly through a specific process called integration or Crossover. Therefore, the offspring inherit some of the characteristics or traits of father and some of the characteristics of mother and represent them.

Roulette wheel

Since the boundaries of Roulette-wheel are marked based on fitness of each of the strings or chromosomes, it is expected that $\sqrt{\frac{FF1}{F}F_i}$ copy of ii^{th} string is produced in mating pool by this operator. The average fitness of chromosomes' population will be calculated as follows.

$$F = n\sum_{0} i = \sqrt{FiF} = \sum_{0} i = 1nF_i \tag{3}$$

Roulette-Wheel is marked by the chromosomes present in current population and based on their fitness values. In other words, the selection probability of each of the chromosomes of the current generation population would be equal to:

$$p_i = F_i p_i \sum ni = 1np_i = F_i \sum i = 1nF_i \tag{4}$$

There have been 20 dimensions(variables) proposed through the GA in Table 1. They are supposed as chromosomes in the GA. Furthermore, dimensions (variables) are written in parentheses for each chromosome and represented in Table 1. In this problem, each chromosome has 20 genes which are in fact the values for DRT, TTD, WFD, VRW, SM, SS, ER, MPS, RM, WPS, FM, PQM, LM, SPMS, SPM, RMC, SUM, SPMT, ES, EI represented in Table 1. Every chromosome gene selected has DRT(device repair time by the maintenance and repair team), TTD (travel time between devices), WFD (weight factor of devices), VRW (Variation reduction in work process), SM (Standardizations of materials), SS (Safety systems), ER (Equipment reliability), MPS (Maintenance planning and scheduling), RM (Resource management), WPS (Work order planning and scheduling) , FM (Financial management), PQM (Process quality maintenance), LM (Lubrication Management), SPMS (Setting up the planned maintenance structure), SPM (Spare parts management), RMC (Reducing maintenance cost activities), SUMS (Strengthening and upgrading maintenance skills), SPMT(Success in using predictive maintenance tools), ES (Employee safety), EI (Environmental impacts).

The Table 2 shows Roulette-Wheel selection operator for each of the living beings or chromosomes present in the population. As it can be observed, the chromosomes 'fitness is different for each one. Since the third chromosome has a higher fitness than other chromosomes in the population, it can be expected that selection operator (reproduction) based on roulette- wheel can choose these chromosomes more than other chromosomes and put them into the (mating pool) tank.

Considering the population in Table 3 select nn living beings or chromosomes from among the current generation population, a number of nn random numbers between zero and one will be produced. Then, for each of the random values produced, the following conditions will be checked: If the random value produced is less than the integrative probability of the nth chromosome, chromosome n will be selected. For example, if the random value produced is less than the integrative probability of the first chromosome (0.04), chromosome 1 will be selected. If not, the next condition will be checked and shown in Table 3.

The ant colony algorithm is inspired by the studies and observations on the ant colony. Studies have shown that ants are social insects that live in colonies and their behavior is more for the survival of the colony than for the survival of one of them. One of the most important and interesting behavior of ants is their behavior to find food, especially how to find the shortest path between food sources and

Population	Fitness
DRT	4
TTD	5
WFD	14
VRW	8
SM	3
SS	6
ER	5
MPS	3
RM	5
WPS	4
FM	2
PQM	5
LM	4
SPMS	6
SPM	4
RMC	5
SUMS	6
SPMT	3
ES	5
EI	3

Table 2: Average fitness for chromosomes population

Population	Fitness probability	Choice probability	Cumulative
DRT	4	0.04	0.04
TTD	5	0.05	0.9
WFD	14	0.14	0.23
VRW	8	0.08	0.31
SM	3	0.03	0.34
SS	6	0.06	0.40
ER	5	0.05	0.45
MPS	3	0.03	0.48
RM	5	0.05	0.53
WPS	4	0.04	0.57
FM	2	0.02	0.59
PQM	5	0.05	0.64
LM	4	0.04	0.68
SPMS	6	0.06	0.074
SPM	4	0.04	0.078
RMC	5	0.05	0.083
SUMS	6	0.06	0.089
SPMT	3	0.03	0.092
ES	5	0.05	.097
EI	3	0.03	1.00

Table 3: Average fitness for chromo somes' population

nest. This type of behavior of ants has a kind of collective intelligence, which has recently attracted the attention of many researchers to produce other meta-heuristic algorithms. This algorithm, which is based on the ability of ants to find the shortest path between the nest and the food source, was first introduced by Dorigo to solve the traveling salesman problem. Six years later, [60] introduced another version of this algorithm called Ant Colony System (ACS), which performed better than the previous version. In ACS, different procedures have been used for local and global updating of pheromones, as well as in selection probability. Other different versions of this algorithm have been introduced to date, such as the elite ant system, the rank-based ant system, and the minimum-maximum ant system. The steps of the ant colony algorithm are as follows:

4.3 Evaluation of ants (initial evaluation)

In this case, we can use two different approaches. Place all the ants in one spot or in different spots. Which method should be used depends on the specific situation. At this stage, this initialization is also done to the pheromones. The pheromone value must be a small integer. This should be done in order to prevent the ants from staying and not moving at the starting point.

4.4 Finding a solution

Because the ACO algorithm tries to imitate the behavior of real ants using the simulation process, the authors of the research use probability function to describe the path. The probability of reaching point j from point (i) is calculated by the following formula.

$$P_{ij} = \begin{cases} \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{h \in tabuK} \tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}} & if \;\; j \notin tabuK \\ 0 & others \end{cases} \tag{5}$$

In this formula where: τ_{ij} refers to the amount of the chemical substance of pheromone in points (i, j) – also it is called an ant sense; η_{ij} is the visibility ratio of points (i, j), known as the ant's eye and is the heuristic of the problem, and is determined as $\eta_{ij} = \frac{1}{d_{ij}}$, through which is the distance between two nodes of i and j; α and β are compatible parameters that represent outstanding roles of the path against the visibility ratio when choosing the next point for movement; $TabuK$ list of visited nodes in the current path form ant's memory. If $\alpha = 0$, the algorithm becomes greedy, so that the selection of the next node does not consider the quantity of pheromones, and as a result the selection of the closest path is prioritized. If $\beta = 0$, the algorithm considers only the number of pheromones without regarding the path length.

4.5 Update of pheromones

When the path follows end by the ants, it is time to change the quantity and number of pheromones. It is comprised of two stages. First, we need to reduce the amount of all pheromones. After that, it is required to update the pheromones connected to the visited points by increasing their amount and quantity. The following formula is utilized to define path evaporation.

$$\tau_{ij} = (1 - \rho)\tau_{ij} \tag{6}$$

Where: ρ refers to the evaporation coefficient of the pheromone. The parameter ρ helps to avoid infinite path accumulations. Thus, this process causes the ants to avoid forgetting the bad paths that they have already discovered. When a point is left unused by ants, the pheromones surface decreases exponentially after each iteration. To consider the evaporation definition, we are required to pdate the number of ants' pheromones. Thus, the path volume is updated using the formula below.

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{7}$$

In this formula, $\Delta\tau_{ij}^{k}$ is the quantity of pheromones located on the points (i, j) transferred by the k^{th} ant. It can be calculated using the following relationship:

$$\Delta\tau_{ij}^{k} = f(x) = \begin{cases} \frac{Q}{LK}, & \text{if an k ege(i, j)in thse tur} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

In this formula Q constant value, which artificially increase pheromones; and L is attributed to the total length of the path, and the better the path, the more pheromones are put on in this path. In general, the points that are used by many ants include part of the short paths, receive more pheromone and thus are more likely to be selected by the ants in the future iteration of this algorithm path. The iteration process stops when at least one of the requirements is met [61]. The repetition process ends when at least one of the requirements is realized [62], [63].

As you know, both algorithms proposed in this article are iterative population-based meta- heuristic algorithms, and these parameters (i.e., the number of iterations and the initial population size) have a direct relationship with the quality of the obtained solutions with respect to the computational time. Usually, the amount of these two types of parameters is directly related to the dimensions of the investigated problem, so that setting small values for these two parameters limits the effective search of the solution spaces, while large sizes reduce the efficiency of the algorithm in achieving optimal solutions in reasonable computing times. So, determining the value of these two parameters depends on the size of the problem as well as the amount of time and cost that the user is willing to spend on them. On the other hand, because in this article, two groups of experimental problems with small, medium and large dimensions have been designed to evaluate the performance of algorithms, and designing experiments for both of these groups for meta-heuristic algorithms is a time- consuming work beyond the scope of this article, and the only difference in the levels of parameters in these two groups of problems is only in the number of repetitions and the amount of the initial population, therefore, in this article, based on trial and error testing for each group of these experimental problems and depending on the reasonable type, fixed values and algorithms for We consider two parameters, the number of repetitions and the size of the initial population. Therefore, by performing a combined multi-factorial test, it is possible to reach optimal levels for other parameters of the algorithm. In this experiment, we consider a small-scale problem and a medium-to-large-scale problem for each experiment, and the final output for each experiment will be the average of the results of these two problems.

4.6 Proposed ant algorithm

- Converting the problem to a directed graph

The first step to implement the algorithm is to transform the optimization problem into a directed graph. The graph used in this research is produced as follows: the tasks that reduce the consequences of failure and increase the life of the company's devices are displayed as a large node. Each big node includes small groups that represent machines. The small groups in a big node are not connected to each other, but each small node in a big node is connected to other small groups in the next big node.

4.7 How to make solution to the problem

To construct a solution, ants travel sequentially from the number one big node to the last big node and meet one of the small nodes at each big node. When an ant completes its journey, the small node it meets at each large node determines the machine on which the task is processed. As a result, the tasks assigned to each device are determined on the graph. But to determine the sequence of tasks assigned to each device, an innovative information is used in this research. Since the objective function of the problem is to achieve the shortest history of work completion time in the PM system, therefore, in order to achieve a favorable solution, it is sufficient to assign the tasks assigned to each machine with a probability according to the law of the longest processing time. Otherwise, we will arrange things completely randomly. In each step of building a solution by ant k, it assigns node i to visitor j in the following ways.

$$j = \begin{cases} argmax_{j\in N_i^k}\{\tau_{ij}^{\alpha}\cdot\eta_{ij}^{\beta}\}, & \text{if } q \leq q_0 \\ j, & \text{otherwise} \end{cases} \tag{9}$$

where q is a random number between $[0, 1]$ and $q_0 \in [0, 1]$ is a parameter whose value is known at first. Otherwise, visitor j is obtained according to the following probability.

$$p_{ij}^k = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{u \in N_i^k} \tau_{iu}^{\alpha} \cdot \eta_{iu}^{\beta}} \tag{10}$$

where τ_{iu} is the amount of pheromone left on node (i, j) in repetition t and η_{ij} is the amount of heuristic information (tendency) to choose node (i, j) whose value is equal to the weighted workload ratio of the visitor v in work place i, that is, $1/F_{iv}$. α and β are the parameters that determine the relative effect of the pheromone power and determine the relative effect of innovative information, respectively, and N_i^k is the set of visitors that can serve node i.

4.8 Evaluation of algorithms

In this section, the performance of two algorithms proposed in this article are compared. As it was said before, in multi-objective optimization problems, unlike single-objective optimization problems, where we always deal with one answer, we deal with answers that none of them have priority over the other, or in other words, the answers do not defeat each other. To evaluate such issues, different quantitative and qualitative criteria have been presented in the literature to date, and we have examined some of these criteria in the literature in this article. In this article, we have tried to consider performance evaluation criteria so that we can compare the performance of two algorithms from different aspects. The quantitative criteria considered in this article include: DRT, TTD, WFD, SM, ER, MPS, WPS, LM, SPMS, SPMT, RMC, SUMS, and quality criteria including: VRW, SS, RM, FM, PQM, SPM, ES, EI. To make these comparisons, in this study, 20 experimental problems in two small scales, including 8 problems, medium to large, 12 problems, were generated and the results of solving the problems by the algorithms were presented in tabular format. Mixed integer programming was used for small dimensions using Lingo software and for medium to large dimensions, the ACO algorithm was used using MATLAB R2012a software, and the average comparative dimensions are reported in the tables.

In order to evaluate the performance of the proposed algorithm, 20 experimental problems in two small scales including 8 small problems and medium to large including 12 production problems and the results of solving the algorithm are presented in a table. In order to evaluate the performance of the algorithm and the quality of the solutions produced by them comparing to the optimal solutions, all 8 small problems were solved by Lingo 9.0 software. It should be noted that the time frame considered for the implementation of the Lingo software is 3 hours and for the problems that cannot be solved by the software in these 3 hours, therefore the best solution is found after 3 hours. In the next step, all 8 small problems and 12 medium to large problems are executed by each of the proposed meta-heuristic algorithms 5 times and the results obtained from solving each example by each algorithm include the worst solution, the average solution and the best solution presented. The obtained solution along with their calculation time are presented in a table. The solution algorithm was implemented in the MATLAB R2012a programming environment and each of these algorithms was implemented in a personal computer.

4.9 Data collection

In order to check the performance of the proposed algorithm, a number of experimental problems in different dimensions are generated completely randomly and the results of these algorithms are compared in terms of the quality of the solution and their computing time. The values of device repair time by the maintenance and repair team, travel time between devices and the weight factor of devices according to the table below are randomly generated by following a uniform distribution and are used as input data for experimental problems. In Table 4, for example: time to repair the devices by the repair and maintenance team type A is between 30 and 50 respectively. Otherwise, a part of device will breakdown or device will suddenly be working and a critical time will be occurred.

Time to repair the devices by the repair and maintenance team type A	U∼[30 50]
Time to repair the devices by the repair and maintenance team type B	U∼[15 30]
Time to repair the devices by the repair and maintenance team type C	U∼[5 15]
Travel time between devices	U∼[7 30]
Weight coefficient of devices	U∼[2 4]

Table 4: Input data values to problems

4.10 Comparing the performance of algorithms for problems with small dimensions

In the following tables, the results of the implementation of the algorithm for problems with small dimensions are reported. As shown in tables 5,6, from 20 test problem ,8 problems for small and 12 problems for medium until large dimensions are assigned. In Table 5, we used small dimensions. We have used mean comparison for small dimensions and medium to large dimensions. For this purpose, the observed means in this tables are root mean square, which has better prediction accuracy than other averaging methods. Also, as the average value increases, its error rate is also greater. Then, by comparing Lingua and the Ant Colony algorithm, it is observed that their situation is worse in dimensions 4 to 8. The reason that the Ant Colony algorithm was used in this research that the average of this method is better compared to the Lingo method. This situation can be seen in Table 5. In Table6, for medium and large dimensions are used MATLABE software. Also, in Table 4, dimensions 9 to 20 were larger, so we could only use the ant colony algorithm and other analyses could not provide a better answer. So, the difference between tables 3 and 4 is in how to use lingo methods and ant colony algorithm in small, medium to large dimensions.

Table 5 shows the results of solving problems with small dimensions by Lingo software as well as ant algorithm. As it is clear from the results, the solutions produced by ant algorithm are of high quality compared to the optimal solutions obtained from Lingo software, so that in all problems, the solutions obtained are the best produced by ant's algorithm. On the other hand, in 6 out of 8 small problems, the solutions obtained from Lingo are found in the worst solution produced by ant's algorithm, which shows the high performance of ant's algorithm in solving problems with small dimensions. In Table5, for medium and large dimensions are used MATLAB software. In additional, In Table 5, the average computing times for each algorithm along with the average solutions produced by them are presented separately for each problem. As it is clear from the results of Table 5, in most cases the computing time required to solve the model by Lingo software is much more than the computing time required to solve the problems by the proposed algorithm. The very small distance between the average solutions obtained from 4 times of running the algorithm with the optimal solutions and the noticeable difference between the solving times by the algorithm and the solving time by Lingo shows the efficiency of this algorithm in solving problems with small dimensions. But in general, the ant algorithm has a better performance in solving problems with small dimensions.

In Tables 5 and 6, the results of running algorithms for problems with small dimensions have been reported. As mentioned before, the average values of each performance measure for each algorithm in each problem are reported. According to the average values obtained in the third to eighth dimensions, the situation in Lingo is worse and it can be concluded that the ACO algorithm is more successful than the Lingo algorithm both quantitatively and qualitatively.

In order to compare the computational time required by the proposed algorithm and the Lingo software in solving problems with small dimensions, the data in Table 6 is drawn as a diagram. Figure 3 shows the exponential trend in increasing the computational time required for Lingo with increasing problem dimensions and the linear behavior in increasing the computational time required for the algorithm with increasing problem dimensions. In additionally, as shown in figure 3, as the problem dimensions increase, the calculation time of the Lingo software increases exponentially, but in ACO is linear.

	Name of Dimension	Problem information	Lingo	Aco		
No.		N x M	Best	Worst	Average	Best
1	VRW	3x2	33.33	33.33	33.33	33.33
2	SS	4x2	45.83	45.83	45.83	45.83
3	RM	5x2	36.33	36.33	36.33	36.33
4	FM	6x2	53.58	53.58	53.58	53.58
5	PQM	6x3	36	37.33	36.66	36
6	SPM	7x2	65.33	65.33	65.33	65.33
7	ES	8x2	82.91	82.91	82.91	82.91
8	EI	8x3	55.5	57.5	56.3	55.5

Table 5: Computational results from solving problems with small dimensions

	Name of Dimension	Problem information	Average		CPU time(s)	
No.		N x M	Lingo	ACO	Lingo	ACO
1	WRW	3 x 2	33.33	33.33	2	3
2	SS	4 x 2	45.83	45.83	7	3
3	RM	5 x 2	36.33	36.33	65	4
4	FM	6 x 2	53.58	53.58	278	8
5	PQM	6 x 3	36	36.66	288	8
6	SPM	7 x 2	65.33	65.33	2035	8
7	ES	8 x 2	82.91	82.91	10800	9
8	EI	8 x 3	55.5	56.3	10800	10

Table 6: Computational times and average solutions obtained from solving problems with small dimensions

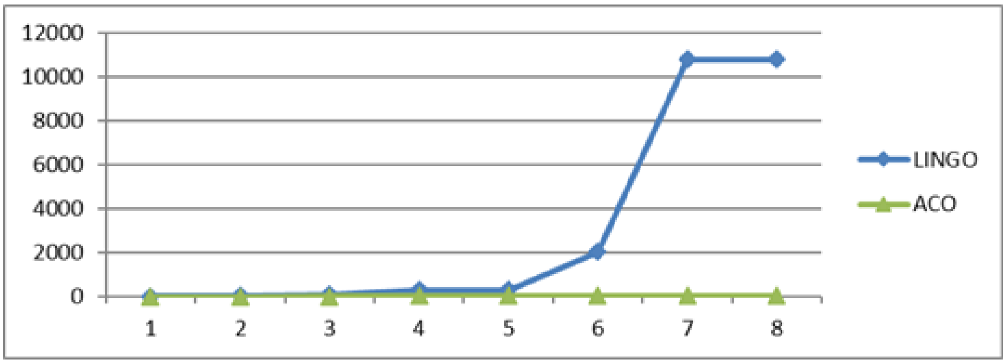

Figure 3: Comparison of computing times required by Lingo software and the proposed algorithm

4.11 Algorithm performance comparison for problems with medium to large dimensions

In order to better and more accurately compare the performance of the proposed algorithm in solving problems with real dimensions, 12 problems with medium to large dimensions were randomly prepared. The calculation results related to solving these problems by solving algorithms can be seen in Table 4. As it is known, the average solutions produced by ant's algorithm are of higher quality.

But in the medium to large dimensions of the performance measurement criteria, the ACO algorithm has a better performance. This superiority is clearly evident in the quantitative measure (RMC). In this criterion, performance measurement in all major problems of ACO algorithm compared to other dimensions has been marked with significant differences. Therefore, the ACO algorithm can be relied on to solve large-scale problems. Therefore, the ACO algorithm can be trusted to solve large-dimensional problems. The computational results for large-dimensional problems are given in Tables 7.

No.	Name of Dimension	Problem	ACO			
		N x M	Worst	Average	Best	Time
9	TTD	12 x 2	116.41	113.46	111.5	11
10	WFD	15 x 3	94.5	92.38	87.83	16
11	SM	18 x 3	112.58	109.21	107.16	21
12	ER	20 x 2	175.43	171.21	167.16	20
13	MPS	20 x 4	107.08	100.34	95.83	22
14	WPS	25 x 3	148.91	145.06	140.5	32
15	LM	30 x 2	250.41	249.23	247.25	40
16	SPMS	30 x 4	143.08	137.79	134.41	44
17	SPMT	40 x 5	158.66	151.46	142.66	48
18	RMC	50 x 2	394	391.14	389.66	60
19	SUMS	50 x 4	227.91	217.12	203.91	61
20	DRT	60 x 4	280.5	274	269.66	73

Table 7: Computational results from solving problems with medium to large dimensions

In order to investigate the efficiency of the proposed algorithms, two sets including small dimensions with 8 problems and medium to large dimensions with 12 problems have been produced. Considering 8 problems for small dimensions and 12 problems for medium to large dimensions, we will have a total of 20 problems. For small dimensions, mixed integer programming and Lingo software have been used to calculate it. MATLAB R2012a software has been used to calculate the to medium large dimensions in the ACO algorithm. According to the results obtained in Table 8, it shows that ACO algorithm has better performance. According to the average values obtained in the last row of each table, it can be concluded that the ACO algorithm is qualitatively more successful than the GA algorithm. Also, in terms of ES (Employee safety) as can be seen from the table, although the ACO model is a suitable method in dealing with problems with small dimensions, but with the increase of the calculation time of the ACO model when the problem becomes larger, the GA method has a more efficient optimization with an average of 5.125.

To solve problems with medium to large dimensions, we use the ACO and GA algorithms, and we consider 12 problems for medium to large dimensions and solve them with each of the algorithms. In addition, in order to compare the algorithms, the results obtained are shown in Table 9. Therefore, the ACO algorithm with an average of 179.36 performs much better than the GA algorithm in dealing with large-dimensional problems. This issue is also true in quantitative indicators. Therefore, the ACO algorithm can be relied on to solve large-scale problems. Also, in the dimensions of SUMS (Strengthening and upgrading maintenance skills) with a computing time of 73 with the best situation in ACO with a value of 269.66 can be seen in Table 9.

Name of Dimension	Problem N x M	GA	LINGO	ACO	CPU(Time)	
					Lingo	ACO
VRW	3 x 2	8	33.33	33.33	3	2
SS	4 x 2	6	45.83	45.83	3	7
RM	5 x 2	5	36.33	36.33	4	65
FM	6 x 2	2	53.58	53.58	8	278
PQM	6 x 3	5	36.66	36 8	288	
SPM	7 x 2	4	65.33	65.33	8	2035
ES	8 x 2	5	82.91	82.91	9	10800
EI	8 x 3	3	56.3	55.5	10	10800
Average Value		5.125		51.10	8.25	30343.37

Table 8: A comparison of GA and Ant colony for small dimension

Name of Dimension	Problem N x M	GA	ACO	Time	Best
DRT	12 x 2	4	113.46	11	111.5
TTD	15 x 3	5	92.38	16	87.83
WTD	18 x 3	14	109.21	21	107.16
SM	20 x 2	3	171.21	20	167.16
ER	20 x 4	5	100.34	22	95.83
MPS	25 x 3	3	145.06	32	140.5
WPS	30 x 2	4	249.23	40	247.25
LM	30 x 4	4	137.79	44	134.41
SPMS	40 x 5	6	151.46	48	142.66
SPMT	50 x 2	3	391.14	60	389.66
RMC	50 x 4	5	217.12	61	203.91
SUMS	60 x 4	3	274	73	269.66
Average		4.9	179.36	36.01	1747.798

Table 9: A comparison of GA and Ant colony for small dimension

4.12 Case Study

In many organizations, the repair and maintenance department based on an empirical rule in order to speed up repairs and maintenance, the repairmen only pay attention to small variables such as the number of devices in each hall and ignore parameters such as the skill level of the repairmen. This will reduce the productivity and motivation of repairmen. In this research, the authors, with optimal routing and taking into account the skill level of the repairmen, leads to an increase in their motivation level and helps to achieve the goals of maintenance and increase the useful life of the company's devices. In this regard, in this section, the problem is examined in a real production unit. The repair and maintenance department of this company has 4 repairmen who have to service 161 devices available at the company level. The problem data is collected experimentally from the company. Due to the large amount of information, we refrain from bringing them in this section. The above problem is solved with the proposed algorithms and the calculation results obtained from solving this practical problem are given in the form of Table 10. According to the results, it is clear that ant's algorithm has significantly obtained solutions with better quality. As you can see, the route is obtained for each algorithm and the sequence of device repair is specified for each repairman. Now, we will examine the results obtained by ant's algorithm. This algorithm has assigned 50 devices to the first repairer, who is the strongest repairer, and assigned 35, 42, and 34 devices to repair subsequent tasks, respectively. In fact, the algorithm has tried to assign devices that are close to each other and located in the same hall to a repairman.

Algorithm	Visitor	Best founded tour	Workload
ACO	V1	67-70-68-64-62-63-66-65-59-49-48-46-47-61-60-57-53-54-55-56-52-58-51-50-71-69-23-21-20-24-25-16-17-15-12-14-13-6-7-5-4-3-10-9-11-93-26-94-27-28	455.9894
	V2	29-30-31-32-33-34-35-36-95-96-97-98-100-99-101-102-103-104-37-38-39-40-41-42-44-43-45-82-81-79-80-78-77-76-75	390.1495
	V3	73-72-74-107-108-109-110-105-111-112-106-117-118-113-114-115-116-123-124-122-121-120-126-127-128-129-125-22-19-18-119-87-86-85-83-84-88-89-90-91-2-92	461.1329
	V4	1-132-133-134-131-135-136-138-137-130-140-139-141-142-144-145-143-146-147-148-150-149-151-153-154-155-152-157-161-158-159-160-156-8	437.8718

Table 10: Computational results obtained from solving the applied problem

5 Conclusion

PM system is one of the important problems of production and operation management. This problem is a type of combined optimization problem that was defined more than 40 years ago and includes designing and optimizing a set of the methods and techniques are for the repair and maintenance of machines that should serve a set of certain devices. Due to the ever-increasing progress of technology and manufacturing industries, as well as the change in the interests and attitude of the societies, knowing the appropriate market and attracting a worthy share from the market and increasing it, has become a problem whose complexity is continuously growing. Solving this problem guarantees the movement towards the survival, dynamism and sustainability of companies and keeping the company's devices ready to work in the current conditions. In order to gain market share and compete in the current turbulent market, all manufacturing companies need to set up a proper maintenance system. Therefore, in order to achieve the above goals, it is necessary to carefully check the proper allocation of devices to the repairmen and the proper routing for each repairman. Therefore, in order to reduce the gap between the theoretical and operational nature of machine repair and maintenance issues in this research, the problem of machine repair by repairmen considering the skill of repairmen and different repair times and repair times between machines in order to create the best work load balance between the repairmen and the maintenance team is considered according to their skill and experience. In the following, a mixed integer programming model is presented for the mentioned problem. Also, meta-heuristic algorithms, i.e. GA and ACO Algorithm; are used to solve the model in practical scales. After adjusting the parameters of the two algorithms, their performance was compared on two levels of experimental problems. Computational results showed the superiority of ants' algorithm in medium to large dimension.

The effectiveness of maintenance implementation was investigated by comparing two algorithms, ACO and GA, of a problem with small and medium to large dimensions, and to solve it and reach the optimal solution, Lingo and MATLAB software were used. The results showed the high ability of implementing maintenance and repair with GA algorithm in solving small problems. In addition, ACO and GA algorithms were applied to medium to large dimension problems using MATLAB software.

In order to improve the efficiency of the machine maintenance system of the manufacturing company, the desired problem has been implemented in this collection. However, in order to carry out future research, various topics are considered in this field. Some of these suggestions are presented as follows: considering the vehicle as determining the appropriate route in repairing large machines; the skill of the repairmen of the repair and maintenance team as an action that varies over time, to examine the learning effect in this parameter. Also considering the time window (the useful life of the devices) for accurate planning to carry out timely repairs and prevent the production line from falling asleep, as well as the dynamics and readiness of the devices in the production line.

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Cite this paper as:
Komari Alaei, M.R.; Rostamzadeh, R.; Koulab, M.; Turskis, Z.; Šaparauskas, J.; Abdsharafat, M. (2025). Implementation of the Maintenance and Repair System Using the Ant Colony Algorithm, *International Journal of Computers Communications & Control*, 20(4), 6888, 2025.
https://doi.org/10.15837/ijccc.2025.4.6888