



Operation Performance Improvement in Automotive Service Station by Minimizing the Wasted Repair Time under Fuzzy Data

Mohamed Khalil^{1,2,*}, Ibrahim Ahmed³, Aziza Attia³

¹Faculty of Engineering -Mataria, Helwan University, Cairo, P.O.11718, Egypt

²Egyptian Academy for Engineering & Advanced Technology, Cairo, Egypt

³Faculty of Education and Technology, Helwan University, Cairo, P.O.11715, Egypt

*Corresponding Author Email: Mohamedibrahim71@yahoo.com

Abstract Customer loyalty is one of the main variables evaluating the performance of every automotive service station. But achieving customer satisfaction is closely linked to repair time, as repair time is known to be one of the metrics that specifically influence customer satisfaction. This work will also concentrate on reducing the repair time for automotive service stations by arranging the maintenance job orders instead of assigning duties to the technicians. The suggested model, Fuzzy procedure after incorporating several adjustments to the general task model to be appropriate for solving the delegated question of repair job instructions from technicians, is used to reduce the total repair time in the automotive service station. The results indicate that the usage of this strategy is an effective way to reduce the repair time, contributing not just to consumer loyalty but also to improvement in the overall income for automotive service station.

Keywords Scheduling repair operation, Optimal Utilization, Repair Time, Fuzzy

1. Introduction

No one can argue that the field of operations workplays a critical role in seeking the best or the most effective answers to realistic challenges in our lives. There are several scholars who have suggested approaches to certain realistic challenges utilizing operations analysis methods such as Raviteja Buddala and Siba Sankar Mahapatra [1] conducted an research an integrated approach for scheduling flexible job-shop using teaching-learning-based optimization method (TLBO) solve the problem of flexible job shop scheduling (FJSP) with a view to minimizing makepan. An FJSP is an extension of the scheduling problem for basic jobs hops. Two sub problems exist in FJSP. They're problem with the routing and sequencing. TLBO also tends to get trapped at the local optimum. A new local search technique accompanied by a mutation strategy (from the genetic algorithm) is integrated into TLBO to improve the quality of the solution and to preserve diversity in the population, respectively. Tests were performed on all instances of Kacem and on the data instances of Brandimarte to measure make pan. Results show that TLBO has outperformed many other algorithms, and can be a competitive approach to FJSP resolution. Marcelo Seido Nagano et al [2]. Carried out An evolutionary clustering search for the total tardiness blocking flow shop problem. Combined with a variable neighborhood search (VNS) for m-machine blocking flow shop scheduling problem with total tardiness minimization. The proposed ECS uses NEH-based procedure to generate an initial solution, the genetic algorithm to produce solutions, and VNS to improve solutions. A number of experiments were conducted to change metaheuristic parameter. ECS is contrasted with ILS, which is considered to be the best metaheuristic problem. Computational tests show superiority of the new method for the measured set of problems. Finally, we are updating 67 new best-knowledged values found by ECS. Su Nguyen et al [3] studied theoretically Genetic Programming for Job Shop Scheduling. The most popular approach to this task is genetic programming (GP). Summarize existing studies



in this field to give the interested researchers an overall picture. More active search for GP selection. Multiple timing decisions and multiple targets. Khaled Elsharkawy [4] studied Solving Fuzzy Multi-Objective Linear Programming Problems with Non Linear Membership Function Using Artificial Neural Networks. (FMOLPP) the cost factors for non-linear membership, then compare the algebraic approach with the time of solution, which suggested solving the above problem using the proposed technique and between the solution using trained feed forward artificial neural networks (FFANN). Choo Jun Tan et al [5] carried out Application of an evolutionary algorithm based ensemble model to job-shop scheduling. As a building block, a modified micro genetic algorithm (MmGA) is used to formulate an ensemble model for multi-objective laboratory optimization problems. Under the Pareto principle of optimality, the MmGA ensemble is able to approximate the optimal solution. To assess the efficacy of the MmGA ensemble; the results show the effectiveness of the MmGA ensemble in undertaking workshop scheduling problems in a positive way. M. S. Osman et al [6] carried out Duality in the fuzzy parametric space for fuzzy parametric nonlinear programming problem. The problem is solved by identifying fuzzy stability groups and presenting the theoretical background through theoretical concepts, limitations and propositions. To be easily drawn to the problems of border fuzzy-parametric double. Po-Hsiang Lu et al [7] carried out a genetic algorithm embedded with a concise chromosome representation for distributed and flexible job-shop scheduling problems. A problem with DFJS involves three scheduling decisions: job-to-cell assignment, sequencing operations, and assignment from operation to machine. Solution by (3D) a- dimensional scheme that is, a dimensional (1D) chromosome space and a dimensional (3D) solution space. By GA J S, We are developing a 1D to 3D decoding method for converting a 1D mutation to a 3D solution. Furthermore, we use a refinement method given a 3D solution to improve the scheduling performance. The results indicated that numerical experiments indicate that GA J S outperforms the IGA the up-to-date best-performing genetic algorithm used to solve DFJS problems. John Park et al [8] studied theoretically an investigation of Ensemble Combination Schemes for Genetic Programming based Hyper-heuristic Approaches to Dynamic Job Shop Scheduling. Systematic analysis is carried out for four popular combination schemes on dynamic JSS, followed by linear combination, weighted majority vote and weighted linear combination, which didn't apply to dynamic JSS. Proposing several measures to analyze the decision-making process in GP evolved ensembles. The results show that the linear combination is generally better than the other combination schemes investigated for the dynamic JSS problem. And the various combination schemes result in significantly different interactions between the ensemble members. Justyna Trojanowska et al [9] carried out the tool supporting decision making process in area of job-shop scheduling known as critical resource, which determines production system efficiency. Implemented in three production companies located in the Greater Poland area. The companies have confirmed the effectiveness of the described tool in supporting production scheduling decision-making. Also, the application is successfully used in job-shop scheduling research. .Set of manufacturing orders is presented as, production order number, operation time, workstation, where an operation is realized, next operation, previous operation. Adrian Pugnaa et al [10] carried out using Six Sigma Methodology to Improve the Assembly Process in an Automotive Company. It has been proven that the implementation of the Six Sigma methodology delivers breakthrough quality improvements in a reasonable short time. The creative solution for improving assembly processes in a Romanian automotive company using the methodology Statistical Thinking and DMAIC Six Sigma. To enable smoother handling, a Poka-Yoke device was installed to signal acoustically and visually when the necessary downforce was achieved, the riveting process was brought into control, the riveting process capacity was significantly improved over the short and long term, Cpk increased from 0.96 to 1.72, Sigma Level increased short-term from 2.9 to 5.2, Sigma Level increased long-term from 1.4 to 3.7, DPMO decreased from 81,000 to 108, improving the riveting process resulted in a 40 per cent reduction in defects, selecting the most suitable supplier resulted in a 30 per cent reduction in defects. Kai Zhou Gao. et.al. [11] carried out an improved artificial bee colony algorithm for flexible job-shop scheduling problem with fuzzy processing time. IABC for FJSP, Extensive computational experiments are performed on eight practical remanufacturing instances. The proposed heuristic rule is tested using five comparison cases, respectively, to reduce the maximum blurred completion time and the maximum blurred machine workload objectives. The IABC algorithm is contrasted with six meta-heuristics for the criterion for maximum fuzzy completion times. For full volatile system workload, the results and comparisons



show that the IABC algorithm can effectively solve FJSP with Fuzzy processing time, IABC algorithm schedules can meet the real-life shop floor requirement. And part of the professional and intelligent scheduling program to support the scheduling and management of remanufacturing. Kai Zhou Gao et al [12] carried out artificial bee colony algorithm for scheduling and rescheduling fuzzy flexible job shop problem with new job insertion. A two-stage algorithm (TABC) with several improvements is used to solve FJSP with Fuzzy processing time and new job insertion restrictions. Several new methods for generating solutions and improving strategies compared to each other. To minimize the maximum blurry completion time. Eight remanufacturing instances are solved with the use of TABC algorithm. Two proposed ABC algorithms with the best performance are compared by five benchmark cases over seven existing algorithms. The results of optimization and comparisons demonstrate the feasibility of the proposed TABC algorithm to solve FJSP. Salwani Abdullah et al [13] carried out Fuzzy job-shop scheduling problems: A review. Reviews the definition of Fuzzy JSSPs, the constraints and targets examined in Fuzzy JSSPs, and the methodologies used in Fuzzy JSSPs resolution. And to study the meta-heuristic algorithms proposed for Fuzzy JSSPs as state-of - the-art algorithms. Such algorithms are analyzed, those algorithms are evaluated in three stages, namely pre-processing, procedures for initialization and algorithms for improvement. This survey will provide suggestions for future studies. Yanmei Hu et al [14] carried out a novel objective function for job-shop scheduling problem with fuzzy processing time and fuzzy due date using differential evolution algorithm. Obtain optimal timetables based on the target features. To solve those objective functions, an updated DE algorithm done built. To illustrate the reliability and comparability of our method, multiple job-shop scheduling problems are tested with fuzzy processing time and fuzzy due date. The possible implementation of the principle of possibilities and need in the real world is shown through the experimental results. Deming Lei [15] studied Fuzzy job shop scheduling problem with availability constraints. To obtain a schedule that maximizes the minimum contract index subject to periodic maintenance, non-recoverable jobs and a blurry due date. By a random key genetic algorithm (RKGA), in which a random key novel is represented, a new decoding approach is being used that combines maintenance operation and discrete crossover (DX). RKGA is applied with the availability constraints and compared to other algorithms to some fuzzy scheduling problem. Computational results indicate that RKGA performs better than other algorithms. M. S. Osman et al [16] studied theory optimal vehicle replacement policy in fuzzy environment these parameters which are dealing with vague and imprecise of the cost of keeping repairing and replacement which are have a great effect on the optimum decision (keep repair or replace). We also introduce a method of transforming the problem to non- fuzzy form, and a real application for modeling and solving a real life problem.

2. Methodology

According to their implementations, there are many examples to reflect the Assignment Problem (AP). Several descriptions of these models will also be given and the general state of the assignment problem will also be provided for use in this research.

2.1. The Classical Assignment Model (CAM)

One of the main premises of the above is that all the functions should be carried out at the same time. Yet, in some situations the workers can be split into divisions or classes, with criteria for grouping either within each category or within classes, owing to customary constraints. Note that the goal here is to find a permutation P (a mission assignment of agents) that minimizes the cumulative sums of assignment values (usually times) over the different sets of m. This objective is to reduce the time at which the last set of tasks is finished if all sets start at the same time, where a set's completion time is the sum of the time of its tasks. Therefore, we have the basic idea of a classic AP inside each set (minimize the sum), while we have the basic idea of a bottleneck AP (minimize the maximum) over the sets.



2.2. Mathematical Model of CAM

$$\begin{aligned}
 & \text{Min } z = \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij} \\
 & \text{Subject to:} \\
 & \sum_{i=1}^n x_{ij} = 1 \quad j = 1, 2, \dots, n \\
 & \sum_{j=1}^n x_{ij} = 1 \quad i = 1, 2, \dots, n \\
 & x_{ij} = 0 \text{ or } 1
 \end{aligned} \tag{1}$$

Where $x_{ij} = 1$ if the machine i is assigned to job j , 0 if not, and c_{ij} is the cost of assigning machine i to job j . The first set constraint ensures that each job is assigned to only a machine and the second set constraint ensures that each machine is assigned to a job.

2.2. The General Assignment Model (GAM)

Most of the classical assignment model (CAM) that allows a machine to be assigned to multiple jobs is the generalized assignment model (GAM). The assumption in this model (GAM) is as in the CAM, but each job will be assigned to one machine. It allows the possibility that a machine may be assigned to do more than one job, while recognizing how much of a machine capacity is used to do each of those jobs. Thus the GAM is an example of a one-to-many assignment model that recognizes capacity limits. Recognizing that a job may use only part of a machine capacity (GAM) rather than all of it as in (CAM), leads to the following model

$$\begin{aligned}
 & \min \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij} \\
 & \text{Subject to} \\
 & \sum_{i=1}^m x_{ij} = 1 \quad j = 1, 2, \dots, n \\
 & \sum_{j=1}^n a_{ij} x_{ij} = b_i \quad i = 1, 2, \dots, m \\
 & x_{ij} = 0 \text{ or } 1
 \end{aligned} \tag{2}$$

Where $x_{ij} = 1$ if the machine i is assigned to job j , 0 if not, and c_{ij} is the cost of assigning machine i to job j . a_{ij} is the amount of machine i 's capacity used if that machine is assigned to job j , and b_i is the available capacity of machine i . The first constraint ensures that each job is assigned to only a machine and the second constraint ensures that the set of jobs assigned to a machine do not exceed its capacity.

2.3. The Proposed Mathematical Fuzzy Assignment Model (PMFAM)

According to a proposed model in this paper which is represented in Fig 1. the objective of the paper is to minimize the repair time of the automotive in service stations in order to maximize the utilization of working time, to increase the labors productivity and to improve the labors efficiency, and on the other hand, increase the level of customer satisfaction, too. The customer satisfaction will be reflected on the higher service station income.



$$\begin{aligned}
 & \text{Min } \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^l \widetilde{t}_{jk}^i x_{jk}^i \\
 \text{Subject to } & \sum_{j=1}^m x_{jk}^i = 1 \quad i = 1, 2, \dots, n \ \& \ k = 1, 2, \dots, l \\
 & \sum_{i=1}^n \sum_{k=1}^l \widetilde{t}_{jk}^i x_{jk}^i \leq \widetilde{T}_j \quad j = 1, 2, \dots, m \\
 & x_{jk}^i = 0 \text{ or } 1
 \end{aligned} \tag{3}$$

Where $x_{jk}^i = 1$ if the labor j is assigned to job k for vehicle i , other wise = 0

\widetilde{t}_{jk}^i is the fuzzy time of assigning labor j to job k for vehicle i

\widetilde{T}_j is the available fuzzy time of labor j 's

The first set constraints ensure that the any job must be finished by only one labor. The second set constraints ensure that any labor can perform more than one job without exceeding the available time for him. Where $x_{jk}^i = 1$ if the vehicle i is assigned to technician j for job k , 0 if not,

labor	jobs					
	1	2	3	.	.	l
1	t_{11}^m	t_{12}^m	t_{13}^m	.	.	t_{1l}^m
2	t_{21}^m	t_{22}^m	t_{23}^m	.	.	t_{2l}^m
.

labor	jobs					
	1	2	3	.	.	l
1	t_{11}^2	t_{12}^2	t_{13}^2	.	.	t_{1l}^2
2	t_{21}^2	t_{22}^2	t_{23}^2	.	.	t_{2l}^2
.

labor	jobs					
	1	2	3	.	.	l
1	t_{11}^1	t_{12}^1	t_{13}^1	.	.	t_{1l}^1
2	t_{21}^1	t_{22}^1	t_{23}^1	.	.	t_{2l}^1
.

Figure 1: Time table for labors according to the required job for each vehicle



The first set of constraints ensures that the any required jobs for any vehicle must be finished by one technician only. The second set of constraints ensures that any technician can perform (use??) more than a vehicle without exceeding the available time for him. $x_{ij} = 1$ if the vehicle i is assigned to technician j , 0 if not. The proposed model considers a nonlinear model because the time is variable multiple with the decision variable, to convert the model from nonlinear to linear model we will put the term $(\widetilde{t}_{jk}^i x_{jk}^i)$ as equal to (y_{jk}^i) and replace the term (\widetilde{T}_j) with the upper boundary (U_j) and lower boundary (L_j) [6]. The proposed model will become as the following.

$$\begin{aligned}
 & \text{Min } \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^l y_{jk}^i \\
 \text{Subject to } & \sum_{j=1}^m x_{jk}^i = 1 \quad i = 1, 2, \dots, n \ \& \ k = 1, 2, \dots, l \\
 & \sum_{i=1}^n \sum_{k=1}^l y_{jk}^i \leq T_j \quad j = 1, 2, \dots, m \\
 & L_j x_{jk}^i \leq \sum_{i=1}^n \sum_{k=1}^l y_{jk}^i \leq U_j x_{jk}^i \quad j = 1, 2, \dots, m \\
 & x_{jk}^i = 0 \text{ or } 1 \forall ijk
 \end{aligned} \tag{4}$$

3. Member ship Function

There are many ships for the member ship function that describe the fuzzy number from this forms

3.1. Generalized fuzzy number

A generalized fuzzy number \widetilde{A} is a fuzzy set defined on \mathbb{R} whose membership functionsatisfies the following properties

- (1) $\widetilde{\mu}_A(x)$ is a continuous mapping from \mathbb{R} to $[0, 1]$.
- (2) $\widetilde{\mu}_A(x) = 0, -\infty < x \leq a$.
- (3) $\widetilde{\mu}_A(x)$ is strictly increasing on $[a, b]$.
- (4) $\widetilde{\mu}_A(x) = 1, b \leq x \leq c$.
- (5) $\widetilde{\mu}_A(x)$ is strictly decreasing on $[c, d]$.
- (6) $\widetilde{\mu}_A(x) = 0, d \leq x < \infty$.

where a, b, c, d are real numbers[22].

3.2. Trapezoidal fuzzy number

A fuzzy set \widetilde{A} defined on \mathbb{R} is called trapezoidal fuzzy number (as shown in Fig. 2) and is denoted by $\widetilde{A} = (a, b, c, d)$ if the membership function of \widetilde{A} is given by

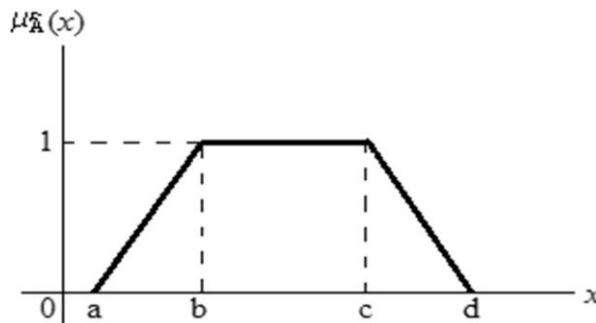


Figure 2: Trapezoidal fuzzy number

Note If b and c are equal, then the trapezoidal fuzzy number becomes a triangular Fuzzy number as shown in Fig. 3 and is denoted as $\widetilde{A} = (a, b, d)$.



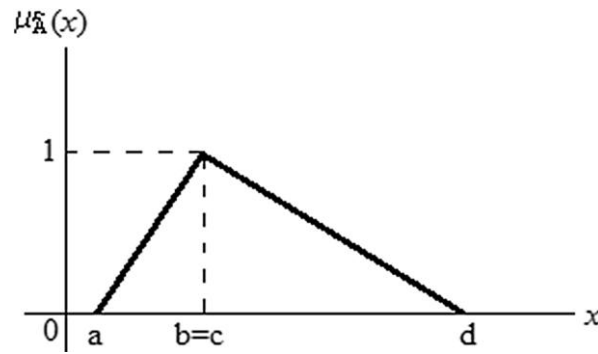


Figure 3: Triangle membership function

4. Application

The proposed mathematical model as equation (4) will be applied to one of the automotive service stations to study its usefulness in term of reducing the repair time in the service centers. The selected automotive service station in this paper is working by booking system so that no vehicle is accepted without pre-booking. This means that the service station knows in advance the required size for the man-hour on the next day. Therefore, this option has been used to schedule the required work to be carried out to maximize the service station efficiency by distributing the vehicles between technicians according to their efficiency in the required jobs per each vehicle. So the distribution will be according to the required repair time for each technician.

4.1. Collected Data

In this paper, we will take a part of the data to check the efficiency of the proposed model. So, we will choose data about one type of vehicles that will enter the service station in the next day and it can generalized after that. The day will be randomly selected and the data will be collected as the following/as shown. Table 1 represents the mean operations time for each technician as the selected operation form the booking list can be summarized to 11 operations required in this day for vehicles by deviation 10% approximately . The number of technicians is 8 technicians and their distribution is illustrated in Table 2 with total repair time 3125 min for all technicians. Table 3 reflects the required operations for each vehicle where the number of vehicles is 19 vehicles. From Table 4 to Table 11, these tables represent the time required to complete the required work for each technician. Table 12 represents the names of the selected operations for the vehicles through this day, and Table 13 shows the workshop capacity in the selected day.

Table 1: Mean Operations Time for Different Technicians by (minutes)

Operation	1	2	3	4	5	6	7	8	9	10	11
Tech											
A	100	75	85	120	110	175	125	115	95	110	120
B	90	65	90	140	120	140	130	110	90	110	130
C	85	80	90	150	125	130	145	100	90	105	125
D	90	75	85	125	115	150	155	125	85	120	135
E	90	60	90	130	110	130	145	100	95	95	125
F	95	65	85	120	125	140	130	110	95	100	120
G	90	65	90	140	120	140	130	110	90	110	130
H	95	65	85	120	125	140	130	110	95	100	120



Table 2: The Required Operations for the Existence vehicles in the Service Station in This Day

Operation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1						√							√						
2					√				√								√		
3		√		√	√									√				√	
4											√				√				
5			√			√		√				√							
6			√																√
7							√			√						√			
8									√								√		
9	√												√					√	
10	√			√															
11		√																	

Table 3: The Actual Distributions for technicians on the vehicles

Vehicle	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
A	√	√																	
B			√	√															
C					√	√													
D							√	√	√										
E										√	√	√							
F													√	√	√				
G																√	√		
H																		√	√

Table 4: The mean wanted time for complete the required works for Technician No. 1

Operation	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									95	110		205
2			85								120	205
3					110	175						285
4			85							110		195
5			75	85								160
6	100				110							210
7							175					175
8					110							110
9		75						115				190
10							175					175
11				120								120
12					110							110
13	100								95			195
14			85									85
15				120								120
16							175					175
17		75						115				190
18			85						95			180
19						175						175

Table 5: The mean wanted time for complete the required works for Technician No. 2

Operation \ Vehicle	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									90	110		200
2			90								130	220
3					120	140						260
4			90							110		200
5		65	90									155
6	90				120							210
7							130					130
8					120							120
9		65						110				175
10							130					130
11				140								140
12					120							120
13	90								90			180
14			90									90
15				140								140
16							130					130
17		65						110				175
18			90						90			180
19						140						140

Table 6: The mean wanted time for complete the required works for Technician No. 3

Operation \ Vehicle	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									90	105		195
2			90								125	215
3					125	130						255
4			90							105		195
5		80	90									170
6	85				125							210
7							145					145
8					125							125
9		80						100				180
10							145					145
11				150								150
12					125							125
13	85								90			175
14			90									90
15				150								150
16							145					145
17		80						100				180
18			90						90			180
19						130						130



Table 7: The mean wanted time for complete the required works for Technician No. 4

Operation \ Vehicle	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									85	120		205
2			85								135	220
3					115	150						265
4			85							120		205
5		75	85									160
6	90				115							205
7							155					155
8					115							115
9		75						125				200
10							155					155
11				125								125
12					115							115
13	90								85			175
14			85									85
15				125								125
16							155					155
17		75						125				200
18			85						85			170
19						150						150

Table 8: The mean wanted time for complete the required works for Technician No. 5

Operation \ Vehicle	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									95	95		190
2			90								125	215
3					110	130						240
4			90							95		185
5		60	90									150
6	90				110							200
7							145					145
8					110							110
9		60						100				160
10							145					145
11				130								130
12					110							110
13	90								95			185
14			90									90
15				130								130
16							145					145
17		60						100				160
18			90						95			185
19						130						130



Table 9: The mean wanted time for complete the required works for Technician No. 6

Operation \ Vehicle	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									95	100		195
2			85								120	205
3					125	140						265
4			85							100		185
5		65	85									150
6	95				125							220
7							130					130
8					125							125
9		65						110				175
10							130					130
11				120								120
12					125							125
13	95								95			190
14			85									85
15				120								120
16							130					130
17		65						110				175
18			85							95		180
19						140						140

Table 10: The mean wanted time for complete the required works for Technician No. 7

Operation \ Vehicle	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									90	110		200
2			90								130	220
3					120	140						260
4			90							110		200
5		65	90									155
6	90				120							210
7							130					130
8					120							120
9		65						110				175
10							130					130
11				140								140
12					120							120
13	90								90			180
14			90									90
15				140								140
16							130					130
17		65						110				175
18			90						90			180
19						140						140



Table 11: The mean wanted time for complete the required works for Technician No. 8

Operation \ Vehicle	1	2	3	4	5	6	7	8	9	10	11	Total mean operation time
1									95	100		195
2			85								120	205
3					125	140						265
4			85							100		185
5		65	85									150
6	95				125							220
7							130					130
8					125							125
9		65						110				175
10							130					130
11				120								120
12					125							125
13	95								95			190
14			85									85
15				120								120
16							130					130
17		65						110				175
18			85							95		180
19						140						140

Table 12 Names of the selected operations

Oper. No.	Operation Description
1	Alternator belt replace
2	Front brake pads R & I
3	Rear brake pads R &I
4	clutch removed+ reinstalled
5	complete service
6	coolant pump R & I
7	Power steering replace
8	Front disc brake replace
9	Normal service
10	Front damper R & I
11	Rear damper R & I

Table 13: Workshop Capacity

m	19 automotive
n	8 Technicians
l	11 operations



4.2. Mathematical Proposed Model

$$\begin{aligned}
 & \text{Min } \sum_{i=1}^n \sum_{j=1}^m \sum_{k=1}^l y_{jk}^i \\
 \text{Subject to } & \sum_{j=1}^m x_{jk}^l = 1 \quad i = 1, 2, \dots, n \ \& \ k = 1, 2, \dots, l \\
 & \sum_{i=1}^n \sum_{k=1}^l y_{jk}^i \leq T_j \quad j = 1, 2, \dots, m \\
 & L_j x_{jk}^i \leq \sum_{i=1}^n \sum_{k=1}^l y_{jk}^i \leq U_j x_{jk}^i \quad j = 1, 2, \dots, m \\
 & x_{jk}^i = 0 \text{ or } 1 \forall ijk
 \end{aligned} \tag{5}$$

By using MATLAB software, the optimal distribution is shown in Table 14, where the total repair time becomes 2734 min instead of 3125 min. That means that the total repair time reduced by 12.5 % approximately.

Table 14: Optimal distribution for technicians on the vehicles, by using MATLAB software

Vehicle Tech. No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1								√			√	√		√					
2													√						
3	√																		√
4						√												√	
5			√						√										
6				√	√														
7							√			√						√			
8		√													√		√		

5. Conclusion

By using the proposed mathematical fuzzy assignment model on a service station in a random day, the labor utilization is improved by 12.5 % approximately. The optimal distribution illustrates that new time can be found for our labors by saving the repair time by redistributing them. This time can be used in new jobs that increase the total income of the service station. In the final, we can say that using the proposed model in service station is considered as a powerful tool for maximizing the labor utilization and will also improve the labor efficiency.

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