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The Balancing of Disassembly Line of Automobile Engine Using Genetic Algorithm (GA) in Fuzzy Environment

Masoud Seidi*
Technical and Engineering Faculty, Ilam University, Ilam, Iran

Saeed Saghari
Saveh Sciences and Researches Branch, Technical and Engineering Faculty, Industrial Engineering Group, Ilam, Iran

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ABSTRACT

Disassembly is one of the important activities in treating with the product at the End of Life time (EOL). Disassembly is defined as a systematic technique in dividing the products into its constituent elements, segments, sub-assemblies, and other groups. We concern with a Fuzzy Disassembly Line Balancing Problem (FDLBP) with multiple objectives in this article that it needs to allocation of disassembly tasks to the ordered group of disassembly Work Stations. Tasks-processing times are fuzzy numbers with triangular membership functions. Four objectives are acquired that include: (1) Minimization of number of disassembly work stations; (2) Minimization of sum of idle time periods from all work stations by ensuring from similar idle time at any work- station; (3) Maximization of preference in removal the hazardous parts at the shortest possible time; and (4) Maximization of preference in removal the high-demand parts before low-demand parts. This suggested model was initially solved by GAMS software and then using Genetic Algorithm (GA) in MATLAB software. This model has been utilized to balance automotive engine disassembly line in fuzzy environment. The fuzzy results derived from two software programs have been compared by ranking technique using mean and fuzzy dispersion with each other. The result of this comparison shows that genetic algorithm and solving it by MATLAB may be assumed as an efficient solution and effective algorithm to solve FDLBP in terms of quality of solution and determination of optimal sequence.

Keywords: Disassembly Line, Balancing, Inverse Logistics, Recycling, Genetic Algorithm (GA)

* Corresponding Author, E-mail: M.Seidi@ilam.ac.ir

1. INTRODUCTION

With ever-growing increase in manufacturing of various products during recent years, the concern has been increased regarding environmental problems as well. The fast and firm ecological regulations and public awareness have caused a great number of manufacturers to recycle their thrown-away products. Recycling, organizing, and execution of all activities have been accompanied with reusing of the wasted materials and products. The product recycling management covers administration of all the thrown and returned products, segments, sub-assemblies, and materials (included in responsibility of the production company). The recycling process aims at conservation of economic and ecologic values as possible that may lead to reducing of wasted landfills and saving energy. Disassembly is the first important step in improving the wasted products and other products at End of Life (EOL) of them. Disassembly may be defined as a purposeful technique to extract valuable parts through a series of operation. Disassembly requires effective design for a disassembly line at large scale. Some of vital decisions should be made in design of line including design of product, selection of process, adjustment of line structure, and line balancing. Whereas many parameters of disassembly system are under uncertainty in real world thus a fuzzy version has been presented from disassembly line balancing problem.

2. A REVIEW ON SUBJECT LITERATURE

The introduction to Disassembly Line Balancing Problem (DLBP) was proposed for the first time by (Gungor and Gupta, 1999) by aiming at minimizing number of work-stations with respect to cycle time. Following to this preamble (Gungor and Gupta, 2002), they suggested a simple heuristic technique to solve DLBP problem and used it to disassembly a Personal Computer (PC) into eight parts with eight tasks. DLBP problem has been noticed further in recent decade and more researchers study on this subject and they have offered and developed several solutions to resolve this problem. Kalayci and Gupta (2011) presented a new approach based on Tabu Search (TS) algorithm to solve DLBP problem. Go *et al.* (2012) posited a model to determine optimal sequence of disassembly using genetic algorithm. In their article, Kalayci and Gupta (2013) have explored Sequence-Dependent Disassembly Line Balancing Problem (SDDLBP) with multiple objectives that required allocation of disassembly tasks to an ordered group of twine disassembly work-stations through satisfying disassembly preference constraints and optimization of efficiency in several tools. They proposed Artificial Bee Colony (ABC) algorithm to solve the given problem (Bentaha *et al.*, 2014) dealt with solving profit-oriented disassembly line balancing problem by considering partial disassembly and presence of risky elements and uncertainty of task times. This study was conducted in order to design a serial line that could acquire maximum profit under uncertainty condition. They employed an AND/OR graph to model disassembly alternatives and with the presence of relations between tasks and sub-assemblies. To cope with uncertainties, a solution was utilized based on Lagrangian Relaxation and Monte Carlo sampling technique. Özceylan *et al.* (2014) present an integrate model that describes optimization of strategic and tactic decisions jointly in Closed-Loop Supply Chain (CSC). The decisions at strategic level are related to the goods in transit in forward and inverse chains and decisions at tactic level correspond to balancing disassembly lines at inverse chain. They have illustrated non-linear programming formulation to the mixed number for the problem. In their study, Bentaha *et al.* (2014) examine disassembly line balancing problem (DLBP) under uncertainty condition in which task times are random variables with known stochastic distributions. To solve this problem, they have used merging Monte Carlo sampling technique algorithm and U-shape algorithm. But, the multiple-objective DLBP problem was proposed by Gungor and Gupta (2002) and it has been proved mathematically as a perfect NP in reference (McGovern and Gupta, 2007) in order to target achieving optimal balance that is high-cost in terms of computations. Perfect NP or hard- NP are proving techniques for this purpose where some levels of problem may not be solvable in realistic time (Tovey *et al.*, 2002). In this study, fuzzy literature possesses fundamental importance in balancing disassembly line. The fuzzy approach was posited for the first time in literature of assembly line balancing in references (Tsujimura *et al.*, 1995) and (Gen *et al.*, 1996) by solving a simple fuzzy assembly line balancing problem for a sample of a plain product. A line balancing problem of a hybrid model was examined with a fuzzy binary linear programming model in reference (Hop, 2006) using heuristic solution approach that dealt with fuzzy processing times. The two-way assembly line balancing problem was solved with multiple fuzzy objectives using an artificial bee colony algorithm in reference (Tapkan *et al.*, 2012) with fuzzy triple objective: Maximization of work discrete index, minimization of total balancing delay, and maximization of line efficiency. Genetic algorithm was utilized for solving fuzzy assembly line balancing problem with multiple objectives type-2 and fuzzy assembly line balancing problem type-E. To the extent this has been explored, only one study has been published by Paksoy *et al.* (2013) about fuzzification of hybrid model of DLBP by means of fuzzy binary target programming. Kalayci *et al.* (2015) have presented Hybrid Discrete Artificial Bee Colony (HDABC) new algorithm to solve multiple objective FDLBP problem. In their study, they have assessed the fuzzy effect on computational complexity of HDABC and compared the quality of solution of their own suggested algorithm with discrete and traditional artificial bee colony algorithm. Avikal *et al.* (2014) posited a hybrid approach of KANO model to select the criteria, Fuzzy AHP process to evaluate weight for each of criteria and M-TOPSIS-based technique for order preference of tasks to attribute them to work-stations, which indicated the success in finding optimal order by means of AND/OR priority relations. Fuzzy numbers have been used to cope with ambiguous and absurd data in this article. Therefore, a fuzzy disassembly line balancing problem (FDLBP) is derived. In this study, disassembly tasks processing times have considered as triangular for membership functions and GAMS software was used to solve FDLBP and also Genetic Algorithm (GA) has been used in MATLAB software and the given results from both software are compared with each other.

2.1 Research Method

Whereas the disassembling process in the real world is under uncertainty, fuzzy numbers are used to deal with the ambiguous data, which in the changed model, the time of activities, cycle time and demand are fuzzy numbers with triangular membership functions. A numerical example related to disassembling the engine automobile with 35 known parts is used for model validation. It is worth noting that so far no study has been done with this volume. To solve the model, a detailed method and a meta-heuristic method (FGA) with fuzzy data has been given. Fuzzy Genetic Algorithm has been not used to solve this problem. In this article, it has been shown that the efficiency of this method is higher than previous methods. In the exact method, target is the definition of a mathematical model for the issue and set the parameters of the program for the rapid solution of the issue. Often, various research methods to a problem are proposed, because each of them may specifically be effective for certain structures of the input data.

The efficiency of a method is usually calculated by the time required for a solution. The exact method of solving the proposed model needed a lot of time to get the results needed. Since the nature of the problem NP-is a complex one, application of approximate methods is inevitable.

Therefore, it was used a meta-heuristic method (FGA) to solve the proposed model in shorter time. Sensitivity analysis of the model for different values to demand, dangerous parts and time was performed, too. Since the disassembly line balancing is one of the most important, sensitive parts in the recovery process, the proposed model can be a start point to achieve increased productivity, reduced costs, optimized sequencing disassembled and the possibility of automation in the future. And also the number of workstations in a disassembly line in reverse logistics can be determined by the use of mathematical programming and providing a new model with multi-objectives, and made the resulting model more realistic, thus arrange an optimal assignment of tasks to workstations. Stages of this research are shown in Figure 1.

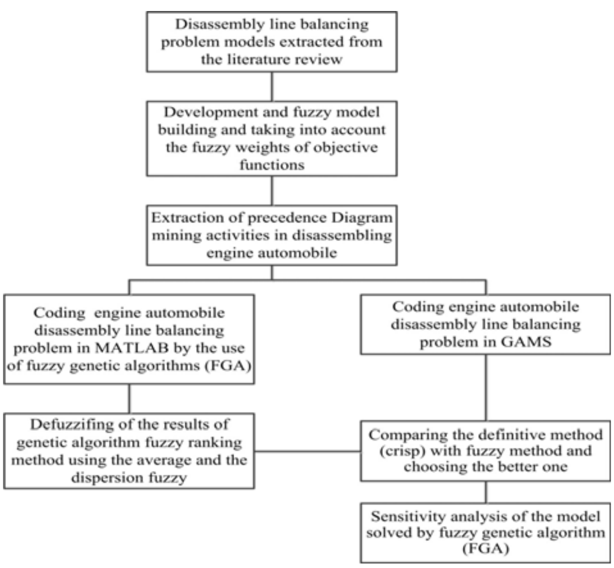

Figure 1. Stages of this research.

3. FUZZY DISASSEMBLY LINE BALANCING PROBLEM (FDLBP)

We directly concern with design of multiple- objective fuzzy disassembly line balancing problem (FDLBP) that is known as single-product. The symbols used in this model are as follows:

3.1 Used Symbols

$\widetilde{CT}$: Cycle time; maximum accessible time in any workstation
$\tilde{d}_l$: Demand; amount of demand in i^{th} part
h_i: Binary; if i^{th} part is not risky; otherwise IP: A set (i_1, i_2) of parts in such a way that i_1 part should be prior to i_2
j: Counting of work stations $(1, \cdots, NWS)$
i: denotes part $(1, \cdots, n)$
N: A set of natural numbers
NWS: Number of the needed work-stations for a sequence of the given solution
PS_i: i^{th} part in a sequence of solution
$\widetilde{ST}_J$: Station time; total needed time for processing in station j
X_{ij}: Allocation of task to work station; if i^{th} part is allocated to j^{th} work station it is 1; otherwise
$\tilde{t}_i$: Time of doing i^{th} activity

3.2 Model of Problem

The assumptions in multiple-objective FDLBP problem are as follows: The rate of supply product is indefinite at end of life (EOL); there is only one type of product in disassembly line; one disassembly task may not be divided between two work stations; the perfect disassembly is done on product; disassembly tasks have been allocated to a tail of work-stations without infringement of preference relations among tasks; a resale value has been assumed for any part that includes its market value and recycling value for materials; the accurate quantity has been identified from any existing part of the product and it is fixed; the presented risky parts are known; and also the presented demand is known with fuzzy value. The multiple-objective mathematical formula was introduced for the first time by McGovern and Gupta (2007) as the final model. Based on the main concepts n the given article, formula of a fuzzy model has been written from this problem in which cycle period is time of work-stations and demand value is of fuzzy type. The offered fuzzy model is as follows:

$$\min f_1 = NWS \tag{1}$$

$$\min f_2 = \sum_{j=1}^{NWS} (\widetilde{CT} - \widetilde{ST}_j) \tag{2}$$

$$\min f_3 = \sum_{i=1}^{n} (i \times h_{ps_i}), \ \ h_{ps_i} = \begin{cases} 1, \text{ risky} \\ 0, \text{ otherwise} \end{cases} \tag{3}$$

$$\min f_4 = \sum_{i=1}^{n} (i \times \tilde{d}_{ps_i}), \ \ \tilde{d}_{ps_i} \in N, \ \forall \ PS_i \tag{4}$$

Subject to:

$$\widetilde{ST}_j \le \widetilde{CT}, \quad j = 1, 2, \cdots, NWS \tag{5}$$

$$\sum_{j=1}^{NWS} x_{ij} = 1, \quad i = 1, \cdots, n \tag{6}$$

$$x_{aj} \le \sum_{j=1}^{NWS} x_{ij}, \quad \forall (a, i) \in IP \tag{7}$$

$$ST_j = \sum_{i=1}^{n} \tilde{t}_1 \times x_{ij}, \ \ j = 1, \cdots, NWS \tag{8}$$

The objective is to minimizes number of work-stations in disassembly line in Eq. (1) at the given multiple-objective model. In Eq. (2), the goal is to minimize total idle time period in all of work-stations and it is intended to create idle time in all of work-stations, which are similar to each other (where $f_2 = 0$ shows full balance) while the goal of Eq. (3) is to delete risky parts at shortest possible time and the Eq. (4) aims at deletion of high-demand parts before low-demand parts in disassembly process. Constraint (5) guarantees that working content of a work-station may not be higher than cycle period. Constraint (6) guarantees all tasks to be allocated to minimum and maximum one work-station (full allocation to any task). Constraint (7) imposes all of constraints in disassembly preference relations between tasks that should be satisfactory and Constraint (8) guarantees the working time in a station to be equal to period of tasks allocated to that station.

4. CASE STUDY

In this article, fuzzy approach is presented for optimization of disassembly line balancing of automobile engine at end of life (EOL) to evaluate potential elements of an automobile in the course of reuse. DLBP problem has been solved for vehicular engine in fuzzy environment in GAMS software as well as using genetic algorithm in MATLAB software. Figure 2(a) and Figure 2(b) displays front and lateral views and Figure 2(c) indicates body of $4G_1$ engine in Mitsubishi vehicle. The main structure of engine body of product (EOL) is shown in Figure 3 where this figure has been developed according to Table 1. This is a table that has been prepared by

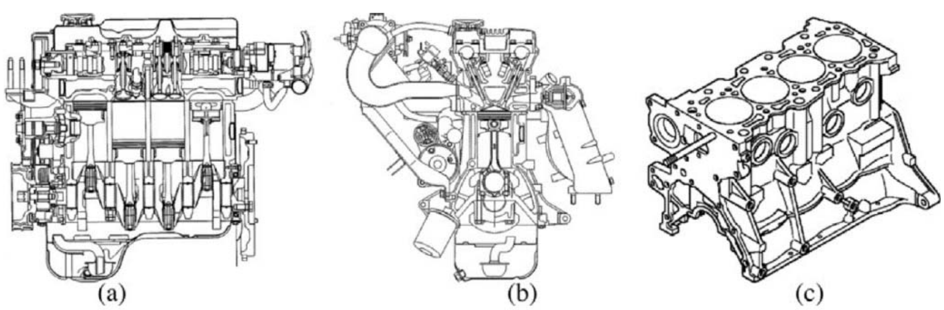

Figure 2. (a) Engine front view, (b) Engine lateral view, (c) Engine body (c) Mitsubishi engines company.

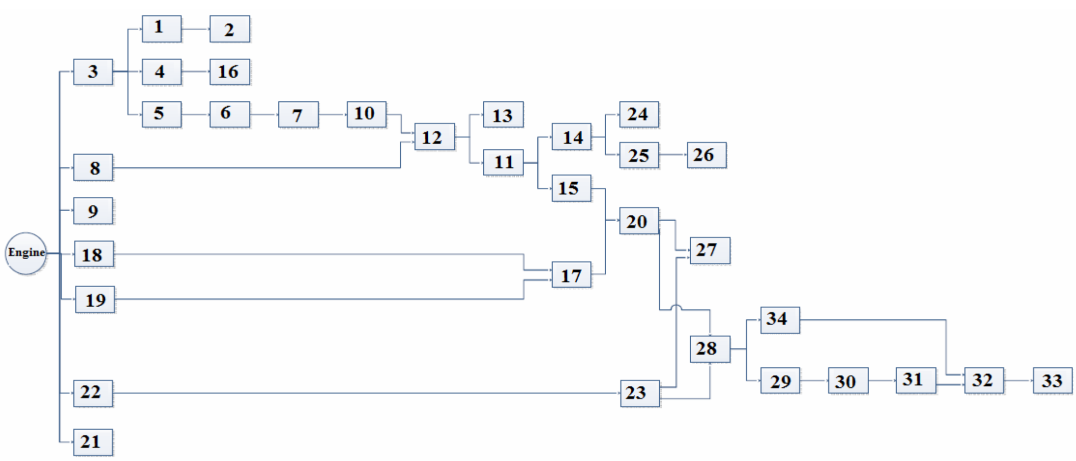

Figure 3. The main structure of product (EOL) e.g. engine body.

guidance manual for engine model ($4G_1$) in Mitsubishi Engines Company. Each and every sub- disassembly has been separated from each other and defined as a single unit.

Therefore, this engine includes 35 marked units (J) represented by integers (1-35). The list of parts appears in Table 1. The existing data in Table (1) in this study included name, prerequisite, time of disassembly and demand for disassembly. In this structure, it aims at achieving the indexed component 35 i.e. engine body.

5. NUMERICAL RESULTS

The suggested model has been encoded in two GAMS and MATLAB software. To examine performance of this model, firstly the known information has been solved by GAMS software. Given fuzzy processing times, the fuzzy data are displayed by means of triangular membership functions. The suggested model has been implemented in a coordinate with specifications of (Intel Core i7-2.20GHz) and with capacity of 12GB. This software

Table 1. The input data for parts in engine model 4G1 from Mitsubishi

Unit	Name	Disassembly prerequisite	Disassembly time	Disassembly demand	Risky
1	Alternator brace	3	(33, 36, 36)	(100, 120, 125)	
2	Alternator	3	(20, 20, 22)		
3	Drive belt		(32, 33, 34)	(380, 390, 405)	
4	Water pump pulley	3	(55, 56, 57)	(530, 540, 560)	
5	Special washer	3	(158, 161, 162)		
6	Crankshaft pulley	3, 5	(9, 11, 12)		
7	Damper pulley	3, 5, 6	(12, 13, 13)		
8	Oil level guide		(12, 12, 13)		
9	Timing belt upper cover		(67, 70, 70)		
10	Timing belt lower cover	7	(139, 141, 145)		
11	Timing belt	9, 10	(40, 42, 45)	(170, 180, 190)	
12	Tensioner spring	9, 10	(34, 35, 36)	(860, 890, 920)	
13	Tensioner	12	(33, 34, 34)		
14	Crankshaft sprocket, flange	7, 10, 11	(70, 72, 72)		
15	Camshaft sprocket	9, 11	(8, 10, 11)		
16	Water pump	3, 4	(54, 55, 56)		
17	Rocker cover, & gasket	18, 19	(10, 10, 12)		
18	Intake manifold		(190, 197, 200)		
19	Exhaust manifold		(136, 142, 144)	(440, 470, 490)	
20	Cylinder head, distributor, camshaft & valves	17, 18, 19	(710, 725, 730)		
21	Oil filter		(59, 63, 64)		
22	Oil pan		(122, 129, 136)		
23	Oil screen	22	(36. 38, 40)		
24	Oil seal	14	(7, 8, 9)		
25	Front case	11, 14	(79, 80, 85)	(990, 1,000, 1,050)	
26	Oil pump	25	(49, 50, 53)		
27	Piston + connecting rod	22, 22, 23	(26, 28, 32)		
28	connecting rod cup	22, 22, 23	(21, 24, 28)		
29	Flywheel	28	(640, 650, 660)		
30	Rear plate	29	(42, 47, 50)		
31	Bell housing cover	30	(31, 33, 37)	(450, 470, 480)	
32	Oil seal case	30, 31, 34	(60, 61, 63)		
33	Rear oil seal	30, 32	(30, 30, 33)		
34	Crankshaft	28	(510, 520, 530)		
35	Block	* full disassembly			

Table 2. Answers to problem per alpha values 0.4 to 1 in GAMS software

alpha	Z1	Z2	Z3	integral	integral×alpha
0.4	127.650	138.120	150.010	0.6258	0.2503
0.5	128.250	138.720	150.610	0.6052	0.3026
0.6	128.850	139.320	151.210	0.5847	0.3508
0.7	129.450	139.920	151.810	0.5642	0.3949
0.8	130.500	140.990	152.890	0.5277	0.4222
0.9	130.650	141.120	153.010	0.5232	0.4709
1	134.370	144.910	156.895	0.3934	0.3934

Table 3. Answers to target functions, fuzzy cycle time solved by GAMS software

Example	f_1	f_2	f_3	f_4	$\widetilde{CT}$
Vehicle engine	6,000	726.250	18.000	44,850.000	(726.500, 726.500, 726.500)

Table 4. The value of hybrid target function with fuzzy weights solved by GAMS software

Target function	f_1	f_2	f_3	f_4
Vehicle engine	(0, 1, 2)	(1.9, 2, 2.1)	(2, 3, 4)	(3.999, 4, 4.001)
Value of hybrid target function	(130.650, 141.120, 153.10)			

has solved the offered model with cycle time (726.500) within time period 300s. According to Table 2, the optimal answer for this model is 0.9 (alpha). The answers of target functions and fuzzy cycle time, fuzzy target value and fuzzy time in work-stations have been presented in Table 3, Table 4, and Table 5, respectively. Table 6 indicates balanced line by this software.

Therefore, the optimal order preference for doing activities to disassembly by means of GAMS software is as follows: 3, 1, 5, 19, 22, 4, 16, 18, 17, 21, 23, 20, 8, 28, 29, 6, 7, 9, 34, 2, 10, 11, 12, 13, 14, 15, 24, 25, 26, 27, 30, 31, 32, and 33.

Table 5. fuzzy time for work stations solved by GAMS software

$\widetilde{ST}_J$	
1	(481.000, 501.000, 512.000)
2	(404.000, 419.000, 429.000)
3	(710.000, 725.000, 701.000)
4	(673.000, 686.000, 701.000)
5	(598.000, 614.000, 625.000)
6	(668.000, 691.000, 728.000)

Table 6. The balanced line using GAMS software

Station	Activity	Number of activity
1	3-1-5-19-22	5
2	4-16-18-17-21-23	6
3	20	1
4	8-28-29	3
5	6-7-9-34	4
6	2-10-11-12-13-14-15-24-25-26-27-30-31-32-33	15

In the suggested model that has been solved using genetic algorithm in MATLAB software, the answer was derived by considering alpha as 0.8, cycle period of 726.500, and within time period of 47.5 where these results are given in Table 7, Table 8, Table 9, and Table 10 respectively.

With respect to Table 10, the optimal order preference for disassembly line balancing by means of MATLAB software is as follows: 21, 22, 19, 3, 5, 6, 7, 10, 9, 12, 11, 14, 25, 26, 4, 1, 18, 17, 20, 23, 28, 29, 30, 31, 13, 34, 8, 32, 27, 24, 2, 16, 15, and 33.

6. DISCUSSION

In this article, we have employed two GAMS and MATALAB software programs to solve fuzzy disassembly line balancing problem (FDLBP). We used fuzzy approach for solving FDLBP to indicate more realistic positions. In this problem, the fuzzy data are fuzzy numbers with triangular membership functions. Now, we should compare the results of two software programs with each other and select the better response to solve FDLBP problem. The results of target functions and cycle time for two software programs are shown in Table 11:

Both of software programs have solved FDLBP problem at the same fuzzy cycle time and with minimum 6 numbers of work station. The answers derived from GAMS software have better in minimization of idle time in work stations and deletion of high-demand parts before low-demand parts in disassembly process, but in third target function where deletion of risky may be assumed as target, the result of MATLAB software can be better. With comparison of these results, it is observed

Table 7. Answers to target functions, fuzzy cycle time and fuzzy target value solved by MATLAB software

Example	f_1	f_2	f_3	f_4	$\widetilde{CT}$
Vehicle engine	6000	726.2560	17.000	48195.000	(726.500, 726.500, 726.500)

Table 8. The value of hybrid target function with fuzzy weights solved by MATLAB software

Target function	f_1	f_2	f_3	f_4
Vehicle engine	(0, 1, 2)	(1.9, 2, 2.1)	(2, 3, 4)	(3.999, 4, 4.001)
Value of hybrid target function	(132.3306, 141.2306, 151.4306)			

Table 11. The target functions, cycle time in GAMS and MATLAB software programs

Min (f)	f_1	f_2	f_3	f_4	$\widetilde{CT}$
GAMS	6.000	726.250	18.000	44850.000	(726.500, 726.500, 726.500)
MATLAB	6.000	726.2560	17.000	48195.000	(726.500, 726.500, 726.500)

Table 9. Fuzzy time for work stations solved by MATLAB software

$\widetilde{ST}_J$	
1	(667.000, 693.000, 710.000)
2	(627.000, 648.000, 666.000)
3	(710.000, 725.000, 730.000)
4	(697.000, 712.000, 728.000)
5	(688.000, 707.000, 728.000)
6	(145.000, 151.000, 163.000)

Table 10. The balanced line using MATALB software

Station	Activity	Number of activity
1	21-22-19-3-5-6-7-10	8
2	9-12-11-14-25-26-4-1-18-17	10
3	20	1
4	23-28-29	3
5	30-31-13-34-8-32	6
6	27-24-2-16-15-33	6

that the answers from two software programs are very close together and sometime equal. Therefore, we compare the fuzzy results from hybrid target function and fuzzy time of work stations by two software programs. The method we employ for comparison of fuzzy results from two software programs is ranking technique using mean and fuzzy dispersion. In this method, fuzzy numbers are compared according parameters including mean value of fuzzy numbers and dispersion of fuzzy numbers. Lee and Li (1988) suggest using extended mean and standard deviation based on measurement of probability for fuzzy consequences to rank fuzzy numbers. They consider two types of probabilistic distributions for fuzzy consequences: uniform distribution and relative distribution. Thus, one of these two types of distribution should be selected for ranking of fuzzy numbers. Using of uniform or relative distribution is optional. In some cases, these two techniques may not be followed by identical results. Lee and Li suggest using relative distribution. In relative distribution, fuzzy mean is close to *m*-value and its standard deviation is smaller than in uniform distribution. Similarly, there is stronger central tendency in relative distribution. Based on theory of Lee and Li, the relative distribution relevant parameters are expressed for calculation of mean and standard deviation of fuzzy number $\tilde{M}$ according to the following relations:

$$\bar{X}_p(\tilde{M}) = \frac{\int_{S(\tilde{M})} x\left(\mu_{\tilde{M}}(x)\right)^2 dx}{\int_{S(\tilde{M})}\left(\mu_{\tilde{M}}(x)\right)^2 dx} \tag{9}$$

Table 11. The target functions, cycle time in GAMS and MATLAB software programs

Min (f)	f_1	f_2	f_3	f_4	$\widetilde{CT}$
GAMS	6.000	726.250	18.000	44850.000	(726.500, 726.500, 726.500)
MATLAB	6.000	726.2560	17.000	48195.000	(726.500, 726.500, 726.500)

Table 12. Ranking of fuzzy numbers

Result of ranking	Comparison of standard deviation values	Comparison of mean values
$\widetilde{M_I} > \widetilde{M_J}$	-	$\bar{X}\left(\widetilde{M_I}\right) < \bar{X}\left(\widetilde{M_J}\right)$
$\widetilde{M_I} > \widetilde{M_J}$	$\sigma\left(\widetilde{M_I}\right) < \sigma\left(\widetilde{M_J}\right)$	$\bar{X}\left(\widetilde{M_I}\right) = \bar{X}\left(\widetilde{M_J}\right)$

Table 13. Sensitivity analysis of the model

main issue	
best solution	(21-22-19-3-5-6-7-10-9-12-11-14-25-26-4-1-18-17-20-23-28-29-30-31-13-34-8-32-27-24-2-16-15-33)
objective function values	Min f = (6, 720.256, 17, 48195)
Hybrid fuzzy objective functions	(132.3306 141.2306 151.4306)
Time solution	47.5 s
h (21) = 0	
best solution	(22-19-3-4-5-6-7-10-9-12-11-14-25-26-18-17-20-23-28-29-30-31-1-34-32-21-24-3-8-16-2-27-33-15)
objective function values	Min f = (6, 720.256, 15, 41248)
Hybrid fuzzy objective functions	(124.8806 133.7806 143.9806)
Time solution	47.5 s
h (22) = 0	
best solution	(21-19-3-4-5-9-6-7-10-12-11-14-25-26-1-22-18-17-23-20-28-29-30-31-34-32-8-33-16-2-24-13-15-27)
objective function values	Min f = (6, 720.256, 15, 41253)
Hybrid fuzzy objective functions	(124.2906 133.1906 143.390)
Time solution	42.3 s
h (26) = 0	
best solution	(22-21-19-3-4-5-9-6-7-10-12-11-14-25-1-18-17-23-20-28-29-30-31-13-34-8-27-32-33-16-26-2-24-15)
objective function values	Min f = (6, 720.256, 3, 44266)
Hybrid fuzzy objective functions	(114.5006 123.4006 133.6006)
Time solution	51.8 s
d (2) = (1,000, 1,000, 1,000)	
The best solution	(22-21-3-2-4-19-5-6-7-9-10-12-11-14-25-26-1-18-23-17-20-28-29-30-31-24-34-8-15-16-13-27-32-33)
objective function values	Min f = (6, 720.256, 19, 52525)
Hybrid fuzzy objective functions	(138.5606 147.4606 157.6606)
Time solution	35.5 s
d (2) = (3,000, 3,000, 3,000)	
best solution	(3-2-22-21-4-19-5-6-9-7-10-12-11-14-25-26-1-18-17-23-20-28-29-30-31-15-13-16-34-24-27-32-33-8)
objective function values	Min f = (6, 720.256, 23, 53743)
Hybrid fuzzy objective functions	(143.8006 152.7006 162.9006)
Time solution	35.2 s
t = 1.05×t	
best solution	(21-22-19-3-4-5-9-6-7-10-12-11-14-25-26-1-18-23-17-20-28-29-30-31-34-16-8-32-2-13-15-24-33-27)
objective function values	Min f = (6, 744.906, 18, 44850)
Hybrid fuzzy objective functions	(133.4406 142.6406 153.6406)
Time solution	34.3 s
t = 0.95×t	
best solution	(21-22-19-3-4-5-6-7-9-10-12-11-14-25-26-1-18-17-20-23-28-29-30-31-34-32-2-13-16-8-33-24-27-15)
objective function values	Min f = (6, 733.256, 18, 44850)
Hybrid fuzzy objective functions	(131.7506 140.3506 149.8506)
Time solution	60.1 s

$$\sigma_p(\tilde{M}) = \left[\frac{\int_{S(\tilde{M})} x^2 \left(\mu_{\tilde{M}}(x)\right)^2 dx}{\int_{S(\tilde{M})} \left(\mu_{\tilde{M}}(x)\right)^2 dx} - \left(X_p(\tilde{M})\right)^2 \right]^{1/2} \quad (10)$$

If $\tilde{M}$ is a triangular fuzzy number, the above formulae are summarized as follows:

$$\bar{X}_p(\tilde{M}) = \frac{1}{4}(l + 2m + n) \quad (11)$$

$$\sigma_p(\tilde{M}) = \frac{1}{80}(3l^2 + 4m^2 + 3n^2 - 2nl - 4lm - 4mn) \quad (12)$$

$$\bar{X}_p(\tilde{M}) = \frac{1}{4}(l + 2m + n) \quad (13)$$

$$\sigma_p(\tilde{M}) = \frac{1}{80}(3l^2 + 4m^2 + 3n^2 - 2nl - 4lm - 4mn) \quad (14)$$

The rule used for ranking them is as follows:

The standard deviation value is used when the mean values of fuzzy numbers are equal. Unlike mean, smaller standard deviation shows better fuzzy number. Now, we intend to calculate mean values of fuzzy numbers in hybrid target function using relative distribution by GAMS and MATLAB software programs. Using Eq. (9), the results are follows:

$$\widetilde{X}(\widetilde{MATLAB}) = (132.3306,\ 141.2306, 151.4306) = 141.5556 \quad (13)$$

$$\widetilde{X}(\widetilde{GAMS}) = (130.650, 141.120, 153.10) = 141.4975 \quad (14)$$

Given that these two results are not the same thus it does not necessitate for calculation of standard deviation. It can be said in ranking of these fuzzy numbers that compared to $\widetilde{X}(\widetilde{GAMS})$, the $\widetilde{X}(\widetilde{MATLAB})$ value is a relatively better fuzzy number. With observation of the conducted comparisons, it can be concluded that using genetic algorithm in MATLAB to solve FDLBP problem will result in answers with higher quality as well as more optimal balancing of vehicle engine disassembly line in fuzzy environment.

7. SENSITIVITY ANALYSIS OF THE MODEL

The model has been implemented for different values of the parameters. The model for parameters that are listed in the table, has been implemented in the Table 13.

The Model has been performed and analyzed according to parameters for dangerous parts, the different demands and tasks for part 2, the operation tasks time and multiplying by the different number (1±0.05). As it is clear, the third objective function value decreases when considering parts with binary values as aero. This is despite the fact that the value of the objective function is as little as possible in h (26) = 0. At the base challenge, the second part is placed in the thirty-second position of disassembly sequence. Therefore, considering the amount of demand for this segment in 1,000, it gets fourth in ran-king in the disassembling sequence. It also rises to the second position, with the increasing amount of demand for this part, (because the third part is a prerequisite to the second part in the order of disassembling). So it is concluded that the model satisfies the requirements of the fourth objective function well. This model also tested for tasks and multiplied by the number (1±0.05), so that the cycle time is increased by multiplying 1.05 times and it has been reduced by multiplying 0.95 times.

8. CONCLUSION

With respect to ever-increasing advancement of technology, it is felt the necessity for further recycling choices before the past time. Reuse, reconstruction, recycling, and disposal processes are deemed as some of the possible alternatives for the product at End of their Life (EOL). Recycling of EOL product may contribute to solve many ecologic problems. Of other aspect of importance of recycling is its economic aspect. The producers can achieve this objective with recycling of EOL products to provide raw materials with lower cost in competitive field. As the first step in recycling of materials and products, disassembly is considered as an important process. A specific disassembly line is the best choice for disassembly trend at large scale. One can create efficient balance between disassembly systems with balancing this line. A fuzzy model has been presented for multiple-objective vehicular engine disassembly (EOL) in this article. Tasks-processing time includes fuzzy numbers with triangular membership functions. The offered model tends to four objectives: (1) Minimization of number of disassembly work-stations; (2) Minimization of sum of idle time period in all of work-stations to ensure from similar idle time at any work-station; (3) Maximization of order preference to remove risky parts within the shortest possible period of time; and (4) Maximization of order-preference in removal of high-demand parts before low-demand parts. This suggested model has been primarily solved by GAMS software and then using genetic algorithm in MATLAB software. This model has been utilized to balance vehicle engine disassembly line in fuzzy environment. The results derived from two software programs have been compared with each other by means of ranking technique using fuzzy mean and dispersion (distribution). The result of this comparison shows that genetic algorithm and solving it by MATLAB may be assumed as an efficient solution and effective algorithm to solve FDLBP in terms of quality of solution and determination of optimal sequence.

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