JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Assignment problem with multiple objectives and its solution using GA Variants

[1]Anita Ravi Tailor,[2]Jayesh M. Dhodiya,

[1]Assistant Professor,[2]Associate Professor
[1]Department of Mathematics,
Navyug Science College, Surat, India.

Abstract : Assignment problem (AP) is commonly employed in industrial organization, manufacturing system, and developing service system to efficiently allocate n activities to n devices in order to optimize total resources. In the multi-objective assignment problem (MOAP), there is a considerable amount of research focused on investigating efficient solutions. This article discusses the use of a non-dominated sorting genetic algorithm (NSGA)-II and III with aspiration level (AL) for solving a multi-objective Assignment problem using an exponential membership function. In this article, the decision-maker (DM) needs to define different aspiration levels (ALs) based on his or her preferences and various shape parameters (SPs) in the exponential membership function (EMF) to illustrate how integrating solutions of the problem can lead to effective allocation plans. This research concludes that the suggested approaches can manage MOAP competently and efficiently with a solid yield, allowing the decision maker (DM) to make a decision based on its aspiration level.
.

***Index Terms* - Multi-objective assignment problem, Aspiration level based NSGA-II, Aspiration level based NSGA-III, Shape parameter**

I. INTRODUCTION

In optimization problems, multi-objective optimization problem (MOOP) deals with optimizing several objective functions that are not compatible. The goal of MOOPs in the Mathematical programming (MP) agenda is to maximize multiple objective functions while considering certain limitations. MOOPs are more pragmatic but also more challenging to resolve compared to the single-objective version. When evaluating various objective functions, a single optimal solution is typically not found. The idea of being optimal comes directly from Pareto dominance, which creates a partial order among the solutions. The Pareto optimal solutions are feasible solutions that cannot be improved in one objective without worsening another objective simultaneously. A decision maker (DM) would opt for an efficient solution (ES) since it embodies all potential trade-offs. Nonetheless, if a significant number.

With a variety of efficient options to choose from, the decision maker struggles to pick their favorite solution among all the efficient ones. Therefore, additional information is necessary to find the best solution in these models, which can be obtained from the subjective preferences of the decision maker. This recommended option is categorized as the "Best Compromise" solution due to the balancing act between multiple objectives. [13].

This article discusses a different method to address a specific instance of the MOOP by using a MOAP. In the classical assignment problem, the goal is to optimize a function with decision variables, whereas in MOAP, there are multiple objectives such as minimizing time, distance, and cost, and maximizing profit, quality, and sales [12, 13].

In a the real-world situation, a deterministic solution may not always be optimal for MOAP due to various contributing parameters. Numerous researchers focused on solving MOAP and offered the optimal solution. Tsai et al. [15] , Przybylski et al. [10] , Bao et al. [1] , Bufardi [3], Kagade and Bajaj [9] , Przybylski et al. [11], De and Yadav [4], Gupta et al. [6], Tiwari et al. [14] , Jayalakshmi and Sujatha [8], Hammadi [7], Belhoul et al. [2] , V. Yadiah. [16] etc have provided the single best compromise solutions for MOAP. Nevertheless, in this instance, the DM is unable to choose alternative solutions that are not dominated. Moreover, let's assume MOAP includes a substantial amount of employees and tasks. In such scenarios, certain methods, such as fuzzy programming technique, become overly complex and time-consuming for computation to solve the problem. Evolutionary genetic methods are especially successful in these areas as they progress toward superior solutions using genetic operators inspired by natural genetic mechanisms. The hybrid genetic algorithm (HGA) approach provides us with one solution. NSGA-II and NSGA-III techniques generate a Pareto front containing all non-dominated solutions on the first front, resulting in DM receiving solutions that fall below its Aspiration Level. This article addresses the shortcomings of current methods by proposing modified solution strategies for MOAP. This study introduces Aspiration Level-based versions of NSGA-II and NSGA-III. objective by providing a set of optimal solutions that cannot be improved in one criterion without compromising another. Enable the Decision Maker (DM) to select the solution according to the needs.

As a result, the this paper propose an approach for creating an initial population in anticipation of using Aspiration Level-based NSGA-II and NSGA-III on MOAP.

II. MATHEMATICAL FORMULATION OF MULTI-OBJECTIVE ASSIGNMENT PROBLEM:

The general mathematical formulation of multi-objective assignment problem is as follows [1-4, 6-16]:

Model-1:

$$\min Z^k(x) = \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}^k x_{ij} \quad , \text{k=1, 2… m}$$

Subject to:

$$\sum_{i=1}^{n} x_{ij} = 1 \text{; j=1, 2, 3… n (only one worker should be assigned the } j^{th} \text{ job)} \qquad (2.1)$$

$$\sum_{j=1}^{n} x_{ij} = 1 \text{; i =1, 2, 3… n (only one job is done by the } i^{th} \text{ worker)} \qquad (2.2)$$

$$x_{ij} = \begin{cases} 1; & \text{if } i^{th} \text{ worker perform to } j^{th} \text{ job} \\ 0; & \text{else} \end{cases} \quad (2.3)$$

$x_{ij} = (x_{11},...,x_{nn})$ is the matrix of decision variable and c_{ij} is the cost of assigning the j^{th} job to the i^{th} worker.

III. SOME PRELIMINARIES

Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS)

PIS and NIS are defined by the minimum and the maximum value of an objective function respectively which are necessary to calculate the membership value for each objective function [5, 12, 13].

The PIS and NIS for objective Z_k is:

$Z_k^{\text{PIS}} = \min Z_k$ $\qquad\qquad$ $Z_k^{\text{NIS}} = \max Z_k$

Subject to constraints (2.1) -(2.3) $\qquad\qquad$ Subject to constraints (2.1) - (2.3)

Exponential membership Function:

In MOOPs, the fuzzy membership functions assist in distinguishing the different aspiration levels (ALs) of DM through the goal functions. Furthermore, the membership function is employed to depict the effectiveness of vague data, incorporating fuzzy numbers from decision-makers and preferences for uncertainty. The exponential membership function (EMF) offers greater flexibility in representing the precision of parameter values compared to other methods. Furthermore, it provides a more precise reflection of reality compared to the linear membership function [5, 13].

If Z_k^{PIS} and Z_k^{NIS} are PIS and NIS of objective Z_k, the EMF for $\mu_{Z_k}^E$ is defined by

$$\mu_{Z_k}^E(x) = \begin{cases} 1; & \text{if } Z_k \le Z_k^{\text{PIS}} \\ \dfrac{e^{-S\psi_k(x)} - e^{-S}}{1 - e^{-S}}, & \text{if } Z_k^{\text{PIS}} < Z_k < Z_k^{\text{NIS}} \\ 0; & \text{if } Z_k \ge Z_k^{\text{NIS}} \end{cases} \quad (3.1)$$

where, $\psi_k(x) = \dfrac{Z_k^{\text{NIS}} - Z_k}{Z_k^{\text{NIS}} - Z_k^{\text{PIS}}}$ and $S \ne 0$ is shape parameter (SP) which specified by DM such that $\mu_{Z_k}(x) \in [0,1]$. The membership function is strictly convex (concave) for $S < 0 (S > 0)$ in [$Z_k^{\text{PIS}}, Z_k^{\text{NIS}}$].

IV. SOLUTION PROCEDURE

This section introduces a AL based NSGA-II and NSGA-III and HGA approaches for MOAP to find out the Pareto front solutions. As well as this approach provides better litheness to solve the MOAP in terms of different variety of ALs for all objective functions.

Steps to find the efficient solution of MOAP using HGA:

Step-1: Consider the multi-objective assignment problem (Model-1).

Step-2: Convert maximum objective function of the problem into minimum form.

Step-3: Find out the positive ideal solution (PIS) and negative ideal solution (NIS) for each objective function.

Step-4: Find fuzzy exponential membership value for Z_K .

Step-5: In this step, multi-objective assignment problem is converted in the single-objective optimization problem (SOP) as follows.

(model-3)

$$\max W = \prod_{k=1}^{m} \mu_{Z_k}$$

Subject to the constraints: (1) – (3)

$$\mu_{Z_k}(x) - \overline{\mu_{Z_k}}(x) \ge 0; \; k = 1, 2, ...m \qquad (4.1)$$

where, $\overline{\mu}_{Z_k}(x)$ is the desired aspiration level of fuzzy goals corresponding to each objective. Above model can be solved by varying aspiration levels of the DM regarding the achievement of various fuzzy goals [Gupta].

Step-6: Find the different assignment plans for the model- 2 which is developed in step-5 using genetic algorithm (GA) with various choices of the shape parameter.

Steps to find the efficient solution of MOAP using Aspiration level based NSGA-II and NSGA-III:

The following is a step-by-step description to find efficient solutions to the MOAP using Aspiration levelNSGA-II and NSGA-III.

Apply the step- 1 to step-4 as discuss above.

Step-5: In this case, use NSGA-II and NSGA-III with different estimates of ALs and different values of SPs to generate the solution sets of **p-1** which satisfied the constraints (1)- (3) and (5).

NSGA-II

NSGA-II is a multi-objective evolutionary algorithm which is based on non-dominated sorting. It can be thought of as an improved form of NSGA. By implementing a superior accounting strategy that lessens the complexity of the classification algorithm without generating each generation, NSGA-II provides a quick domain-less classification approach. Depending on the level of non-domination, the NSGA-II operates on a population of size. The NSGA-II approach indicates the property of elitism and does not require any sharing parameters. The crowding distance operator is used for the diversity preservation process. Additionally, it is computationally quick.

To understand the concept of NSGA-II, first we discuss its two main operator: Non-dominated sorting, , Crowding distance tournament selection operator.

Aspiration level based NSGA-II:

Deb et al. [17] have invented a novel NSGA-II approach to produce a Pareto frontier. In this method, no DM is required to prioritize the objective function; therefore, DM gets solutions that are below its AL. In order to overcome this, we have enhanced the NSGA-II by adding a constraint

$\mu_{z^k}(x)-\overline{\mu_{z^k}}(x)\geq 0;\ k=1,2,...,m...$ (4.2)

where $\overline{\mu}_{z^k}(x)$ is given AL corresponding to k^{th} objective function and x is one solution, to satisfies the DM's AL. The enhanced version of NSGA-II is called Aspiration level based NSGA-II

The Steps of AL based NSGA-II

Step-1: Initialize with crossover probability, mutation probability, number of iterations, population size.

Step-2: Generate the initial population P_t for MOAP.

Step-3: Apply non-dominated sorting with crowded comparison operator on P_t

Step-4: Apply genetic operators like crossover and mutation on P_t to get offspring population Q_t

Step-5: Combine population $R_t = P_t \cup Q_t$

Step-6: Apply non-dominated sorting with crowded comparison operator on R_t

Step-7: Display the results.

If obtained solutions are efficient then stop the process otherwise repeat the step 3 to 7.

NSGA-III

The selection process of NSGA-III differs somewhat from that of NSGA-II. For many objective problems, selection mechanism of the NSGA-II is the crowding distance measure which performs poorly. As a result, the selection mechanism in NSGA-III is improved by adopting a more methodical approach to choosing the set of reference points to be utilized in each generation. To guarantee variety in the resulting solutions, NSGA-III makes use of a predetermined set of reference points. Nevertheless, the selected reference points can either be provided preferentially by the user or specified in a systematic manner [16].

The steps of Aspiration levelbased-NSGA-III

Step-1: Initialize with crossover probability, mutation probability, number of iterations, population size.

Step-2: Generate the reference points.

Step-3: Generate the initial population P_t for MOAP.

Step-4: Apply non-dominated sorting with crowded comparison operator on P_t

Step-5: Apply genetic operators like crossover and mutation on P_t to get offspring population Q_t

Step-6: Combine population $R_t = P_t \cup Q_t$

Step-7: Apply non-dominated sorting with crowded comparison operator on R_t

Step-8: Normalize the R_t and associate the R_t with reference point.

Step-9: Apply the Niche Preservation.

Step-10: Display the results.

If obtained solutions are efficient then stop the process otherwise repeat the step 4 to 10.

If DM approved the achieved solution sets then terminate the solution procedure otherwise change the SPs, ALs and reiterate the step-1 to 5 till an agreeable ES sets are achieved.

V. MULTI-OBJECTIVE ASSIGNMENT PROBLEM AND ITS SOLUTIONS:

The three objective assignment problem has been referred from the article of V. Yadiah. [16] which is given as follows:

$$\min Z_1 = 9x_{11} + 7x_{12} + 4x_{13} + 6x_{14} + 12x_{21} + 5x_{22} + 5x_{23} + 8x_{24} + 9x_{31} + 9x_{32} + 9x_{33} + 11x_{34} + 2x_{41} + 7x_{42} + 11x_{43} + 8x_{44}$$

$$\min Z_2 = 2x_{11} + 1x_{12} + 8x_{13} + 2x_{14} + 9x_{21} + 9x_{22} + 1x_{23} + 8x_{24} + 8x_{31} + 9x_{32} + 5x_{33} + 6x_{34} + 1x_{41} + 5x_{42} + 4x_{43} + 9x_{44}$$

$$\min Z_3 = 1x_{11} + 1x_{12} + 1x_{13} + 5x_{14} + 7x_{21} + 5x_{22} + 5x_{23} + 9x_{24} + 1x_{31} + 7x_{32} + 5x_{33} + 7x_{34} + 1x_{41} + 3x_{42} + 5x_{43} + 3x_{44}$$

Subject to the constraints:

$$\sum_{i=1}^{4} x_{ij} = 1 \text{ , } j = 1,2,3,4$$

$$\sum_{j=1}^{4} x_{ij} = 1 \text{ , } i = 1,2,3,4$$

$$x_{ij} = \begin{cases} 1 \text{ if } i^{th} \text{ person is assigned } j^{th} \text{ job} \\ 0 \text{ if } i^{th} \text{ person is not assigned } j^{th} \text{ job} \end{cases}$$

Where cost unit is defined in thousands, time unit is defined in weeks and quality levels are defined as 1, 3, 5, 7 and 9.

To determine set of efficient solutions of MOAP using AL based NSGA-II, some following aspects of parameters for the given problem are summarized as follows: number of populations: 100, number of iterations: 100, P_m:0.5, P_c: 0.5, number of division=5 and for NSGA-III, some aspects of parameters are: number of populations: 100, number of iterations: 100, P_m:0.5, P_c: 0.5 number of division=5.

After forming the MOAP, PIS and NIS for $Z_i; i = 1,2,3$ are shown in table-5.1 which are useful to construct the EMF $\mu_i; i = 1,2,3$ for each objective.

Table-5.1: The PIS and NIS of each objective function

Objective	Cost	Time	Quality
PIS	22	9	10
NIS	41	35	24

The set of efficient solutions by Aspiration levelbased NSGA-II and NSGA-III and HGA are reported in tables-5.2, 5.3, 5.4, 5.5 and 5.6 for different estimates of SP which indicated by the DM.

Table-2: Optimal assignment plans-1

AL: $\left(\bar{\mu}_{Z_1}(x), \bar{\mu}_{Z_2}(x), \bar{\mu}_{Z_3}(x)\right) = (0.9, 0.85, 0.8)$, SP: $(K_1, K_2, K_3) = (-5, -5, -5)$			
Result obtained using Aspiration level based NSGA-II			
Z_1	Z_2	Z_3	Allocations
22	13	18	$x_{14} = x_{23} = x_{32} = x_{41} = 1$
22	17	16	$x_{14} = x_{22} = x_{33} = x_{41} = 1$
22	24	14	$x_{14} = x_{22} = x_{31} = x_{43} = 1$
25	9	14	$x_{12} = x_{23} = x_{34} = x_{41} = 1$
29	19	10	$x_{12} = x_{23} = x_{31} = x_{44} = 1$
Result obtained using Aspiration level based NSGA-III			
22	13	18	$x_{14} = x_{23} = x_{32} = x_{41} = 1$
22	17	16	$x_{14} = x_{22} = x_{33} = x_{41} = 1$
22	24	14	$x_{14} = x_{22} = x_{31} = x_{43} = 1$
25	9	14	$x_{12} = x_{23} = x_{34} = x_{41} = 1$
Result obtained using GA			
25	9	14	$x_{12} = x_{23} = x_{34} = x_{41} = 1$

Table-5.3: Optimal assignment plans-2

AL: $\left(\bar{\mu}_{Z_1}(x), \bar{\mu}_{Z_2}(x), \bar{\mu}_{Z_3}(x)\right) = (0.65, 0.7, 0.75)$, SP: $(K_1, K_2, K_3) = (-3, -1, -2)$			
Result obtained using Aspiration level based NSGA-II			
Z_1	Z_2	Z_3	Allocations
22	13	18	$x_{14} = x_{23} = x_{32} = x_{41} = 1$
22	17	16	$x_{14} = x_{22} = x_{33} = x_{41} = 1$
25	9	14	$x_{12} = x_{23} = x_{34} = x_{41} = 1$
29	19	10	$x_{12} = x_{23} = x_{31} = x_{44} = 1$
Result obtained using Aspiration level based NSGA-III			
22	13	18	$x_{14} = x_{23} = x_{32} = x_{41} = 1$
22	17	16	$x_{14} = x_{22} = x_{33} = x_{41} = 1$

25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$
Result obtained using GA			
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$

Table-5.4: Optimal assignment plans-3

AL: $\left(\bar{\mu}_{Z_1}(x),\bar{\mu}_{Z_2}(x),\bar{\mu}_{Z_3}(x)\right)=\left(0.7,0.9,0.8\right)$, SP: $\left(K_1,K_2,K_3\right)=\left(-2,-1,-3\right)$			
Result obtained using Aspiration level based NSGA-II			
Z_1	Z_2	Z_3	Allocations
22	13	18	$x_{14}=x_{23}=x_{32}=x_{41}=1$
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$
Result obtained using Aspiration level based NSGA-III			
22	13	18	$x_{14}=x_{23}=x_{32}=x_{41}=1$
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$
Result obtained using GA			
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$

Table-5.5: Optimal assignment plans-4

AL: $\left(\bar{\mu}_{Z_1}(x),\bar{\mu}_{Z_2}(x),\bar{\mu}_{Z_3}(x)\right)=\left(0.9,0.75,0.85\right)$, SP: $\left(K_1,K_2,K_3\right)=\left(-1,-2,-3\right)$			
Result obtained using Aspiration level based NSGA-II			
Z_1	Z_2	Z_3	Allocations
22	13	18	$x_{14}=x_{23}=x_{32}=x_{41}=1$
22	17	16	$x_{14}=x_{22}=x_{33}=x_{41}=1$
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$
Result obtained using Aspiration level based NSGA-III			
22	13	18	$x_{14}=x_{23}=x_{32}=x_{41}=1$
22	17	16	$x_{14}=x_{22}=x_{33}=x_{41}=1$
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$
Result obtained using GA			
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$

Table-5.6: Optimal assignment plans-5

AL: $\left(\bar{\mu}_{Z_1}(x),\bar{\mu}_{Z_2}(x),\bar{\mu}_{Z_3}(x)\right)=\left(0.7,0.6,0.55\right)$, SP: $\left(K_1,K_2,K_3\right)=\left(-1,-1,-1\right)$			
Result obtained using Aspiration level based NSGA-II			
Z_1	Z_2	Z_3	Allocations
22	13	18	$x_{14}=x_{23}=x_{32}=x_{41}=1$
22	17	16	$x_{14}=x_{22}=x_{33}=x_{41}=1$
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$
29	19	10	$x_{12}=x_{23}=x_{31}=x_{44}=1$
Result obtained using Aspiration level based NSGA-III			
22	13	18	$x_{14}=x_{23}=x_{32}=x_{41}=1$
22	17	16	$x_{14}=x_{22}=x_{33}=x_{41}=1$
25	9	14	$x_{12}=x_{23}=x_{34}=x_{41}=1$
Result obtained using GA			

25	9	14	$x_{12} = x_{23} = x_{34} = x_{41} = 1$

Table-5.2 shows that AL based NSGA-II gives Pareto optimal sets of 5 solutions while AL based NSGA-III gives Pareto optimal sets of 4 solutions for (0.9, 0.85, 0. 8) ALS and (-5, -5, -5) SPs. Similar Tables-5.3, 5.4, 5.6 and 5.7 show the Pareto optimal sets of MOAP's solution for different estimates of ALS and different values of SPs using Aspiration Level based NSGA-II and NSGA-III. In solving the above problem. NSGA II also provides more options for the DM to choose a solution that represents their aspiration level. The DM may choose any Pareto-optimal solution that satisfies their requirements since all of the alternatives from the Pareto optimum set which are equally important and non-dominated.

VI. COMPARISON

Table-6.1 compares the results obtained from using linear membership function, HGA, Aspiration Level-based NSGA-II, and NSGA-III for MOAP. Table-6.1 represents that HGA provides a unique solution while AL based NSGA-II and NSGA-III provide Pareto fronts with different ALs and SPs for MOAP and which satisfies DM's AL. from table-6.1 it can be seen that using linear membership function provide single solution.

Table-6.1: Comparison of different approaches of MOAP

Case No.	Linear membership function	Aspiration level	Shape parameter	HGA	Aspiration Level based NSGA-II	Aspiration Level based NSGA-III
1	(25, 9, 14)	(-5, -5, -5)	(0.8, 0.7, 0.9)	(25, 9, 14)	(22, 13, 18), (22, 17, 16), (22, 24, 14), (25, 9, 14), (29, 19, 10)	(22, 13, 18), (22, 17, 16), (22, 24, 14), (25, 9, 14)
2		(-3, -1, -2)	(0.65, 0.7, 0.75)	(25, 9, 14)	(22, 13, 18), (22, 17, 16), (25, 9, 14), (29, 19, 10)	(22, 13, 18), (22, 17, 16), (25, 9, 14)
3		(-2, -1, -3)	(0.7, 0.9, 0.8)	(25, 9, 14)	(22, 13, 18), (25, 9, 14)	(22, 13, 18), (25, 9, 14)
4		(-1, -2, -3)	(0.9, 0.75, 0.85)	(25, 9, 14)	(22, 13, 18), (22, 17, 16), (25, 9, 14)	(22, 13, 18), (22, 17, 16), (25, 9, 14)
5		(1, -1, 1)	(0.7, 0.6, 0.55)	(25, 9, 14)	(22, 13, 18), (22, 17, 16), (25, 9, 14), (29, 19, 10)	(22, 13, 18), (22, 17, 16), (25, 9, 14)

VII. CONCLUSION:

This paper provides a Pareto optimal sets for MOAP using Aspiration Level based NSGA-II and NSGA-III with different estimates of aspiration levels and different shape parameters. In a single simulation run, both Aspiration Level based NSGA II and NSGA III offer various solutions, and also NSGA II does so in less iteration than NSGA III and offers more Pareto optimal set overall.

ACKNOWLEDGEMENTS

Anita R. Tailor thanks research project (No. UGC/18475/2021) sponsored by IRP-UGC section, Veer Narmad South Gujarat University, Surat, India for financial assistance.

REFERENCES

[1] BAO, C.-P., T SAI, M., AND TSAI, M.- I., (2007). A new approach to study the multi-objective assignment problem. WHAMPOA-An Interdisciplinary Journal 53 123–132.

[2] BELHOUL, LYES, LUCIE GALAND, AND DANIEL VANDERPOOTEN.(2014) "An efficient procedure for finding best compromise solutions to the multi-objective assignment problem." *Computers & operations research* 49: 97-106.

[3] BUFARDI,(2008) A. On the efficiency of feasible solutions of a multicriteria assignment problem. Open Operational Research Journal 2, 25–28.

[4] DE, P., AND YADAV, B. (2011) An algorithm to solve multi-objective assignment problem using interactive fuzzy goal programming approach. International Journal of Contemporary Mathematical Sciences 6, 34 , 1651–1662.

[5] DHODIYA, J. M., & TAILOR, A. R. (2016). Genetic algorithm based hybrid approach to solve fuzzy multi-objective assignment problem using exponential membership function. *SpringerPlus*, *5*(1), 2028.

[6] GUPTA, P., M EHLAWAT, M. K., AND MITTAL , G.(2013) A fuzzy approach to multi criteria assignment problem using exponential membership functions. International Journal of Machine Learning and Cybernetics 4, 6, 647–657.

[7] HAMMADI, ABDUL MUNAAM KADHEM.(2017) "Solving multi objective Assignment problem using Tabu search algorithm." *Global Journal of Pure and Applied Mathematics* 13.9: 4747-4764.

[8] JAYALAKSHMI, M., AND V. SUJATHA.(2018) "A new algorithm to solve multi-objective assignment problem." *International journal of pure and applied mathematics* 119.16: 719-724.

[9] KAGADE, K., AND BAJAJ, V.(2009) Fuzzy approach with linear and some non-linear membership functions for solving multi-objective assignment problems. J Adv Comput Res 1, 14–17.

[10] PRZYBYLSKI, A., G ANDIBLEUX, X., AND EHRGOTT, M.(2010) A two phase method for multi-objective integer programming and its application to the assignment problem with three objectives. Discrete Optimization 7, 3, 149–165.

[11] PRZYBYLSKI, A., G ANDIBLEUX, X., AND EHRGOTT, M. (2005) The bi objective assignment problem. Tech. rep., Research Report,.

[12] TAILOR, A. R., & DHODIYA, J. M. (2016). Genetic algorithm based hybrid approach to solve multi-objective assignment problem. *Int J Innov Res Sci Eng Technol*, *5*(1), 524-535.

[13] Tailor, Anita R., and Jayesh M. Dhodiya.(2021) "Multi-objective assignment problems and their solutions by genetic algorithm." *Computational Management: Applications of Computational Intelligence in Business Management*. Cham: Springer International Publishing, 409-428.

[14] TIWARI, A. K., TIWARI, A., SAMUEL, C., AND PANDEY, S. K.(2013) Flexibility in assignment problem using fuzzy numbers with nonlinear membership functions. International Journal of Industrial Engineering & Technology 3, 2 , 1–10.

[15] TSAI, C.-H., W EI, C.-C., C HENG, C.-L., ET AL. (1999) Multi-objective fuzzy deployment of manpower. International Journal of the Computer, the Internet and Management 7, 2 , 1–7.

[16] Yadaiah, Ventepaka, and V. V. Haragopal.(2016) "Multi-objective optimization of time-cost-quality using Hungarian algorithm." *American journal of operations research* 6.1: 31-35.

[17] K. Deb, S. Agrawal, A. Pratap and T. Meyarivan,(2000) A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, International Conference on Parallel Problem Solving from Nature, 849-858