APPLICATION OF FUZZY LINEAR PROGRAMMING APPROACH FOR SOLVING MIX-PRODUCT SELECTION PROBLEM

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Abstract

In this paper, the modified SMF system is used in the real MPS problem. This problem occurs in the production planning process where the decision maker plays an important role in making decisions in an uncertain environment. As researchers, we are trying to find the best solution for the final decision maker. SMF analyzed FLP production equipment using data actually collected from chocolate production companies. The problem of MPS incompatibility has been described. The aim of this article is to find the best UOP with high satisfaction and nonsense as the main thing. Since there are so many decisions to make, the best UOP table is defined in terms of insensitivity and satisfaction to find a solution with a high UOP level and a high level of satisfaction. OF indicates that a high UOP will not lead to a high level of satisfaction. The results of this work suggest that the best decision is based on the negative impact on the FS of the MPS. In addition, a high level of UOP is achieved when the blur is low.

Keywords: Linear Programming, Uncertainty, Fuzzy constraint, Mix-Product Selection.

Abbreviations:

MPS	:	mix product selection
FLP	:	fuzzy linear programming
SMF	:	s-curve membership function
FO	:	fuzzy outcome
FS	:	fuzzy system
UOP	:	units of product

1. Introduction

Non-SMF conversion function is used for problems related to FLP. The function S can be applied and tested for its effectiveness by applied pressure. In this example, the S function is applied to make a decision after binary, such as the number of technologies and equipment, of which MPS is complex. Solutions thus obtained can provide the decision maker and the coordinator for the final implementation. The wording described in this article is just one of the three FPS words that actually have an application. The above FPS term is considered to be the real-life situation when it comes to making chocolate. Data for this problem are provided in the database of Choco man Inc, USA. Choco man manufactures chocolate bars, candies and wafer using a variety of ingredients and formulas. The goal is to use the modified S function as a system to get the best UOP through the FLP system [1-3]

Compared with this FLP system. The recommended method is based on its relationship with the decision maker, developer and researcher to find satisfactory solutions for the FLP problem. In the decision-making process using the FLP model, modifications and source software can be complex, rather than providing exact numbers as in the net LP model. For example, machine hours, work, requirements, etc. and manufacturing, which is not always good, due to insufficient information and uncertainty among potential importers in the environment. Therefore, they should be considered as non-essential components and the FLP problem can be solved by using the FLP method. The problem of non-compliant MPS has been described. The aim of this article is to find the best UOP with high satisfaction and nonsense as the main thing. This problem is considered because all the parameters such as technology and hardware changes are uncertain. This is considered to be a major overall problem that includes 29 barriers and 8 barriers. Since there are so many decisions to make, the best UOP table is described for uncertainty and satisfaction to find a solution. with the highest UOP level and the highest satisfaction. It should be borne in mind that a high UOP does not mean it will lead to a high level of satisfaction. The best UOP was calculated at the satisfaction level using the FLP method. OF indicates that a high POU will not lead to a high level of satisfaction. The results of this work suggest that the best decision is based on the negative impact on the FS of the MPS. In addition, high levels of UOP are obtained when blur is low in the system [4-25].

2. Methodology of MF

A general model of classical LP is formulated as,

$$Max(w) = dy \quad \text{standard formulation;}$$

Subject to,

$$By \le c; y \ge 0 \tag{1}$$

Where d and y are the m-part vector, d is the m-part vector, and B is $n \times m$ matrix. Since we live in an uncertain environment, the number of objective functions (d), the number of matrix technologies (B) and the variability of assets (d) are complex. Therefore, an infinite number can be displayed, so that the problem can be solved by the FLP system. FLP problems are designed as follows:

$$Max(w) = d^* y \quad \text{The Fuzzy formulation;}$$

Subject to,

$$B^* y \le c^*; y \ge 0 \tag{2}$$

where x is the vector of the decision change; $B^*, c^* \,\&\, d^*$ are zero numbers; The function of addition and multiplication is explained by fact that in-depth numbers are derived from the extension principles of Li [26]; Njikọ Inequalities are provided by some relationship and work objectives, w must take into account the given LP problem. The approach of Mohammed [27] is being considered to solve the problem of FLP 2 depletion., which means that the solution will probably be to some satisfaction. First, design the team function for the zero parameter of $B^*, c^* \& d^*$. Here, non-existent team functions, such as logic, are used. vb_{kl} represents the work of members; vc_k and vd_l is the numerical function of matrix B for $k = 1, 2, \ldots.n \& n = 1, 2, \ldots.m$, c_k is the numerical variable for $k = 1, 2, \ldots.n$ and d_l are the integers of purpose point w for $l = 1, 2, \ldots.m$.

Then, with the appropriate change in the concept of agreement between the non- b_{kl}^* numbers; c_k^* and d_{kl}^* & l, words for b_{kl}^*, c_k^* and d_l^* will be obtained. When an agreement between b_{kl}^*; The solution c_k^* and d_l^* will be [28];

$$v = vd_l = vb_{kl} = vc_k \tag{3}$$

for all $k = 1, 2, \ldots.n \& l = 1, 2, \ldots.m$

Therefore, we can obtain;

$$D = pd(v), B = pb(v) \& c = pc(v) \tag{4}$$

Where $v \in [0,1]$ in $pd, pb \& pc$ are distinct functions [29] of $vd, vb \& vc$ respectively. Equation (2) would be,

$$Max(w) = [pd(v)]y \quad \text{Fuzzy formulation;}$$

Subject to,

$$Max(w) = [pd(v)]y; y \geq 0 \tag{5}$$

First, create a group function for the complex part of $B^* \& c^*$. Here, non-uniform functions are used as S-curve function [30]. vb_{kl} represents the work of members and vc_k, where b_{kl} is the coefficient of matrix B for $k = 1, 2, \ldots.29$, $l = 1, 2, 3, \ldots.8$ and c_k is the material variable for $k = 1, 2, \ldots.29$. Group function is also obtained for b_k and beard time, $c_k b$ to $c_k c$ for c_k^*. Similarly, we can create team work for a number of non-core technologies and their production [31]. Due to the high cost of production and the need to meet certain production and demand conditions, the problem of inefficiency arises in the manufacturing process. This problem also arises in the production of chocolate when deciding on the combination of ingredients to create different types of products. This is called here the choice of product mix [32]).

3. The Fuzzy MPS

There are products that can be made by mixing different ingredients and using k type processing. It is expected that the infrastructure will be massive. There are also some restrictions by the retail department, such as the requirement for the product mix, the requirement of the main product line, as well as the minimum and maximum query for each product. Not everything that is needed in these circumstances is obvious. It is important to achieve maximum UOP and satisfaction using the FLP method. Since the number of technologies and equipment changes is running high, the results of the UOP would be foolish. FLP problem, customized in size. 2 can be written:

$$Max(w) = \sum_{l=1}^{8} y_l$$

Subject to,

$$\sum_{l=1}^{8} b_{kl}^{*} y_l \le c_k^{*}; \tag{6}$$

where $y_l \ge 0, i = 1,2,3,...8,\ b_{kl}^{*}\ \&\ c_k^{*}$ are fuzzy parameters.

3.1 Fuzzy Resource Variable

For an interval, $c_k b \prec c_k \prec c_k c$,

$$\begin{aligned} b_{c_k} &= \frac{c}{1 + De^{\left(b\left(c_k - c_k^b\right)/c_k^c - c_k^b\right)}} \\ e^{\frac{\beta\left(c_k - c_k^b\right)}{\left(c_k^c - c_k^b\right)}} &= \frac{1}{D}\left(\frac{c}{\theta_{c_k}} - 1\right) \\ \frac{\beta\left(c_k - c_k^b\right)}{c_k^c - c_k^b} &= \ln\left[\frac{1}{D}\left(\frac{C}{\theta_{c_k}}\right) - 1\right] \\ c_k &= c_k^a + \frac{1}{D}\left(\frac{c_k^c - c_k^b}{\beta}\right)\ln\left[\frac{1}{D}\left(\frac{C}{\theta_{c_k}}\right) - 1\right] \end{aligned} \tag{7}$$

Since c_k is a non-trivial material change in size. 7, it is found vc_k. Therefore

$$cc_k^{*} = c_k^b + \left(\frac{c_k^c - c_k^b}{\beta}\right)\ln\left[\frac{1}{D}\left(\frac{C}{\theta_{c_k}}\right) - 1\right] \tag{8}$$

3.2 Fuzzy Constraints

The products, materials and equipment requirements are shown in Tables 1 as well as 2, respectively. Tables 3 as well as 4 provide the mix size and use the required material to make each product.

Table 1: *Products Demand*

Items	Fuzzy Interval $(\times 10000)$ units
Milk Chocolate, (200 gram)	[450-575) Gram
Milk Chocolate, (50 gram)	[750-950) Gram
Crunchy Chocolate, (200 gram)	[350-450) Gram
Crunchy Chocolate, (50 gram)	[550-700) Gram
Chocolate with Nuts (200 gram)	[250-325) Gram
Chocolate with Nuts (50 gram)	[450-575) Gram
Chocolate Candy	[150-200) Gram
Wafer	[350-450) Gram

Table 2: *Material and Ease of Access*

Raw Material	Fuzzy Interval (x1000 units)
Coco (Kilo Gram)	[75-125) Kilo Gram
Milk (Kilo Gram)	[90-150) Kilo Gram
Nuts (Kilo Gram)	[45-75) Kilo Gram
Sugar (Kilo Gram)	[150-450) Kilo Gram
Flour (Kilo Gram)	[15-25) Kilo Gram
Aluminum Foil (Kilo Gram)	[375-625) Kilo Gram
Paper (Per Feet Square)	[375-625) Per Feet Square
Plastic (Per Feet Square)	[375-625) Per Feet Square
Cooking (Ton per H)	[750-1250) Ton Per H
Mixing (Ton per H)	[150-250) Ton Per H
Forming (Ton per H)	[1125-1875) Ton Per H
Grinding (Ton per H)	[150-250) Ton Per H
Wafer Making (Ton per H)	[75-125) Ton Per H
Cutting (H)	[300-350) H
Packaging 1 (H)	[300-500) H
Packaging 2 (H)	[900-1500) H
Labor (H)	[750-1250) H

There are two unclear barriers such as access to the equipment and restrictions on the capacity of the equipment. These barriers are inevitable for any object and property depending on the consumption of the property, to trade and acquire property. These selections are based on the FLP resolution of Choco man Inc. Decision changes for the FPSP are defined as:

$y_1 =$ 250 grams of chocolate milk to be produced (in 1000)

$y_2 =$ 250 grams of chocolate milk to be produced (per 1000)

$y_3 =$ Chocolate Crispy of 250 grams to be produced (in 1000)

$y_4 =$ 100 grams of Chocolate Crispy to be produced (in 1000)

$y_5 =$ Chocolate with 250 grams of fruit to produce (in 1000)

$y_6 =$ Chocolate contains 100 grams per gram to produce (in 1000)

$y_7 =$ Chocolate candies will be produced (in 1000 packages)

$y_8 =$ Chocolate wafer production (in 1000 packages)

$$y_1 \leq 0.6 y_2 \tag{9}$$

$$y_3 \leq 0.6 y_4 \tag{10}$$

$$y_5 \leq 0.6 y_6 \tag{11}$$

The required product line is key. Total sales of confectionery products and wafers should not exceed 15% (uncertain value) of total confectionery product.

Table 3: *Mixing Proportions*

Material Required per 1000 units	Product types (Fuzzy interval)							
	AMC 150	AMC 50	ACC 150	ACC 50	ACN 150	ACN 50	Candy	Wafer
Coco (Kilo Gram)	[60-90)	[20-45)	[105-130)	[25-60)	[150-250)	[0-0)	[1200-1400)	[150-300)
Milk (Kilo Gram)	[0-0)	[0-0)	[60-90)	[0-0)	[78-101)	[35-80)	[230-500)	[0-0)
Nuts (Kilo Gram)	[325-456)	[78-105)	[230-280)	[34-87)	[0-0)	[0-0)	[110-230)	[73-130)
Sugar (Kilo Gram)	[172-201)	[0-0)	[78-99)	[0-0)	[321-436)	[103-120)	[0-0)	[54-90)
Flour (Kilo Gram)	[0-0)	[0-0)	[120-150)	[0-0)	[450-487)	[245-298)	[1001-1200)	[540-670)
Aluminum Foil (Kilo Gram)	[110-165)	[78-95)	[0-0)	[0-0)	[330-420)	[110-154)	[0-0)	[0-0)
Paper (Per Feet Square)	[156-185)	[0-0)	[190-245)	[0-0)	[100-150)	[56-89)	[0-0)	[0-0)
Plastic (Per Feet Square)	[0-0)	[0-0)	[170-240)	[40-82)	[510-725)	[120-179)	[0-0)	[0-0)

Table 4: *Facility Usage*

Facility Usage Required Per 1000 Units	Product types (fuzzy interval)							
	AMC 150	AMC 50	ACC 150	ACC 50	ACN 150	ACN 50	Candy	Wafer
Cooking (Ton per H)	[0.60-0.90)	[0.20-0.45)	[0.105-0.130)	[0.25-0.60)	[0.150-0.250)	[0-0)	[0.1200-0.1400)	[0.150-0.300)
Mixing (Ton per H)	[0-0)	[0-0)	[0.60-0.90)	[0-0)	[0.78-0.101)	[0.35-0.80)	[0.230-0.500)	[0-0)
Forming (Ton per H)	[0.325-0.456)	[0.78-0.105)	[0.230-0.280)	[0.34-0.87)	[0-0)	[0-0)	[0.110-0.230)	[0.73-0.130)
Grinding (Ton per H)	[0.172-0.201)	[0-0)	[0.78-0.99)	[0-0)	[0.321-0.436)	[0.103-0.120)	[0-0)	[0.54-0.90)
Wafer Making (Ton per H)	[0-0)	[0-0)	[0.120-0.150)	[0-0)	[0.450-0.487)	[0.245-0.298)	[0.1001-0.1200)	[0.540-0.670)
Cutting (H)	[0.110-0.165)	[0.78-0.95)	[0-0)	[0-0)	[0.330-0.420)	[0.110-0.154)	[0-0)	[0-0)
Packaging 1 (H)	[0.156-0.185)	[0-0)	[0.190-0.245)	[0-0)	[0.100-0.150)	[0.56-0.89)	[0-0)	[0-0)
Packaging 2 (H)	[0-0)	[0-0)	[0.170-0.240)	[0.40-0.82)	[0.510-725)	[0.120-0.179)	[0-0)	[0-0)
Labor (H)	[0.325-0.456)	[0.78-0.105)	[0.230-0.280)	[0.34-0.87)	[0-0)	[0-0)	[0.110-0.230)	[0.73-0.130)

Table 5: *Optimal UOP with a satisfaction degree*

Number	Satisfaction degree (**θ**)	Optimal UOP (w^*)
1	7.562	2438.54
2	14.076	2500.51
3	15.2145	2615.83
4	16.1148	2651.25
5	18.057	2701.67
6	24.8497	2845.48
7	28.9782	2848.79
8	30.3968	2889.39
9	31.7572	2923.44
10	42.6513	2955.9
11	50.0115	2965.11
12	52.1911	3001.89
13	52.8741	3057.48
14	59.6383	3152.55
15	63.3374	3160.55
16	63.538	3180.37
17	64.8241	3204.67
18	70.4424	3250.39
19	85.5813	3277.92
20	95.4286	3344.58

4. Results

The FPS problem is solved by using MATLAB and its LP application. It provides complexity and a degree of satisfaction. The LP application has two extras in addition to the non-existent. There is an output w^*, the best UOP.

Table 6: *The vagueness β as well as objective value w^* with $\theta = 50\%$*

Vagueness **β**	UOP w^*
1	2465.54
3	2533.72
5	2568.99
7	2631.09
9	2730.54
11	2740.35
13	2778.95
15	2784.04
17	2833.00
19	3011.15
21	3037.45
23	3080.78
25	3223.61
27	3239.79
29	3282.03
31	3352.45
33	3368.74
35	3438.1
37	3446.69

Table 7: *Optimal UOP* w^*

w^*	Vagueness β			
θ	1	3	5	7
7.562	2421.27	2478.47	2594.46	2488.84
14.076	2514.88	2502.54	2673.13	2509.44
15.2145	2638.86	2623.91	2765.32	2574.27
16.1148	2639.8	2632.57	2780.56	2604.7
18.057	2668.82	2675.98	2797.33	2618.06
24.8497	2686.3	2680.99	2919.95	2621.45
28.9782	2753.94	2747.67	2930.67	2652.31
30.3968	2827.54	2773.03	3028.05	2723.29
31.7572	2870.88	2807.2	3189.58	2753.75
42.6513	2957.06	2847.5	3230.2	2810.63
50.0115	2960.57	3010.7	3234.95	2838.32
52.1911	2981.24	3017.36	3248.8	2843.2
52.8741	3078.7	3080.9	3297.06	3039.16
59.6383	3079.57	3086.95	3298.37	3157.71
63.3374	3132.07	3162.39	3334.88	3206.49
63.538	3273.09	3202.78	3415.55	3315.88
64.8241	3443.79	3348.41	3426.19	3411.56
70.4424	3479.39	3434.25	3470.15	3476.37

Different standards of Chocolate production are transferred to the toolbox. The answer can be listed in the following tables. From Table 5, it can be seen that a high level of satisfaction provides a high UOP. But the best solution to the above problem is at a satisfaction rate of 50%, or 2833 minutes. From the tables below, we conclude that within the objective, w^* is an ever-increasing function. Increased [33].

Table 8: *Optimal UOP* w^*

w^*	Vagueness β			
θ	9	11	13	15
7.562	2517.93	2511.75	2700.82	2626.7
14.076	2555.17	2562	2817.03	2713.6
15.2145	2610.27	2712.45	2818.6	2730.28
16.1148	2694.71	2735.65	2917.06	2735.94
18.057	2704.95	2778.61	3015.94	2814.01
24.8497	2768.05	2785.92	3017.65	2843.42
28.9782	2803.52	2982.47	3019.4	2857.43
30.3968	2912.9	3162.64	3200.54	2919.49
31.7572	2959.22	3205.75	3210.48	2936.06
42.6513	3006.57	3238.42	3211.28	3082.57
50.0115	3106.2	3252.29	3236.27	3155.49
52.1911	3110.49	3312.54	3276.6	3166.6
52.8741	3155.25	3326.07	3285.56	3215.15
59.6383	3206.75	3341.22	3292.6	3306.44
63.3374	3367.82	3383.69	3312.35	3339.97
63.538	3432.71	3393.02	3319.99	3353.86
64.8241	3461.5	3394.43	3341.83	3462.87
70.4424	3478.85	3435.72	3421.66	3493.17

Table 9: *Optimal UOP* w^*

w^*	Vagueness β			
θ	17	19	21	23
7.562	2560.71	2591.74	2598.75	2569.53
14.076	2577.5	2681.47	2671.48	2712.04
15.2145	2827.45	2695.28	2725.3	2774.99
16.1148	2857.61	2745.12	2898.84	2857.97
18.057	2877.99	2760.14	2919.28	2910.07
24.8497	3081.74	2770.16	2962.64	2962.97
28.9782	3093.67	2858.84	2989.96	2977.2
30.3968	3157.45	3063.62	3018.63	2983.99
31.7572	3202.92	3087.9	3020.53	2988.83
42.6513	3279.76	3093.95	3025.39	3012.8
50.0115	3289.08	3100.34	3089.09	3119.28
52.1911	3329.94	3206.97	3105.94	3133.89
52.8741	3339.61	3249.02	3118.94	3212.27
59.6383	3343.42	3287.02	3159.21	3267.98
63.3374	3362.92	3361.71	3185.11	3331.74
63.538	3373.1	3417.77	3275.53	3457.72
64.8241	3440.06	3434.14	3397.49	3486.65
70.4424	3492.01	3471.26	3495.27	3498.94

Table 10: *Optimal UOP* w^*

w^*	Vagueness β			
θ	25	27	29	31
7.562	2557.26	2509.77	2624.58	2522.45
14.076	2639.95	2531.72	2637.73	2547.82
15.2145	2727.12	2561.53	2645.54	2584.66
16.1148	2785.23	2610.31	2745.36	2750.06
18.057	2845.05	2680.12	2766.93	2756.62
24.8497	2879.51	2758.1	2778.77	2762.94
28.9782	2937.4	2800.6	2817.91	2832.69
30.3968	2967.17	2840.55	2893.03	2886.01
31.7572	3057.98	2846.94	2961.62	2938.18
42.6513	3110.12	2866.61	3012.12	3001.32
50.0115	3128.99	2880.25	3060.57	3044.8
52.1911	3139.91	2957.15	3075.73	3135.83
52.8741	3240.09	3012.5	3126.45	3297.11
59.6383	3259.24	3066.82	3170.93	3305.56
63.3374	3263.83	3118.69	3292.42	3313.34
63.538	3378.55	3132.87	3296.45	3384.03
64.8241	3422.86	3324.07	3375.38	3404.9
70.4424	3483.18	3350.47	3470.84	3428.67

Table 11: *Optimal UOP* w^*

w^*	Vagueness β			
θ	33	35	37	39
7.562	2522.48	2523.96	2533.43	2519.95
14.076	2532.12	2608.62	2618.64	2611.46
15.2145	2571.52	2618.64	2717.62	2615.81
16.1148	2712.13	2739.13	2749.95	2652.37
18.057	2916.79	2771.39	2778.74	2857.52
24.8497	2943.77	2797.06	2979.54	2891.37
28.9782	3088.17	2828.98	3023.91	2963.05
30.3968	3126.97	2886.21	3082.34	3010.27
31.7572	3130.92	2887.8	3171.68	3020.85
42.6513	3144.28	2901.63	3220.44	3041.08
50.0115	3183.95	2934.68	3236.11	3068.4
52.1911	3202.9	3052.3	3264.69	3102
52.8741	3213.79	3204.34	3330.91	3109.29
59.6383	3342.85	3264.08	3393.05	3214.24
63.3374	3361.04	3270.6	3426.9	3242.07
63.538	3403.39	3377.37	3432.62	3352.56
64.8241	3406.28	3467.32	3455.09	3392.32
70.4424	3492.01	3471.26	3495.27	3498.94

4.1 UOP w* for different vagueness values

Reasonable solutions and some uncertainties in the zero parameter of the technical rate and the hardware change are $=50\%$. Thus, the results for the 50% satisfaction level for $1 \le \beta \le 39$ and the principles corresponding to w^* are shown in Table 6. OFs of UOP reduce β imprecision and increase of the nonlinear parameter of the number of technologies. and asset exchange. This is clearly shown in Table 6. Table 6 is very important for the decision maker when choosing UOP so that the result is a perfect level.

4.2 Output for $\theta, \beta \,\&\, w^*$

The results in the table below show that when the inaccuracy of the increase results in a small UOP.

Table 12: w^* *w.r.to* $\beta \,\&\, \theta$

Satisfaction degree (θ)	Vagueness (β)	Optimal UOP (w*)
7.562	1	2500.51
14.076	3	2615.83
15.2145	5	2651.25
16.1148	7	2701.67
18.057	9	2845.48
24.8497	11	2848.79
28.9782	13	2889.39
30.3968	15	2923.44
31.7572	17	2955.9
42.6513	19	2965.11
50.0115	21	3001.89
52.1911	23	3057.48
52.8741	25	3152.55

59.6383	27	3180.37
63.3374	29	3204.67
63.538	31	3250.39
64.8241	33	3277.92
70.4424	35	3338.54
83.3374	37	3344.58

It is also seen that SMF has a variety of standards that provide possible solutions with some satisfaction. Also, the link between w^*, θ is provided in Tables 7, 8, 9, 10 and 11. This is clearly shown in Table 6. Table 6 is very important for the decision maker when choosing UOP so that the result is a perfect level. From Tables 7, 8, 9, 10 and 11, we find that for each type of satisfaction θ, the optimal UP w^* decreases as the endpoint increases between 1 and 37. Similarly, with any positive value, the optimal UOP increases. as the degree of satisfaction increases. Table 12 is the result of the diagonal pattern of w^* in Table 6. The results of this result show that: when the inaccuracies are low $\beta = 1,3\,\&\,5$, UOP w^* is best. reached the lowest satisfaction level, $\theta = 7.5\%$, $\theta = 14.1\%$ and $\theta = 15.2\%$. When the odds are high at $\beta = 33,35\,\&\,37$, UOP w^* is best reached with high satisfaction level, i.e., $\theta = 64.8\%, \theta = 70.4\%\,\&\,\theta = 83.3\%$.

5. Selection of Parameter β and Decision Making

In order for the decision maker to get the best results for the UOP w^*, the researcher creates a production table. From the table above, the decision maker can select the negative value according to his preference. Hair volume is divided into w^* in three parts, namely short, medium and high. It can be slightly modified if the input data for the number of technologies and hardware changes. It can be called a bunch of empty vanities. The decision can be made by the decision maker by choosing the best UOP for w^* and providing solutions for its implementation.

5.1 Discussion

The results show that the POU minimum is 2,755.4 with a maximum of 3,034.9. It can be seen that when the understanding is between 0 and 1, the maximum value of w * 3 034.9 is obtained by the minimum value. Similarly, when over 39, the minimum gain of w * 2,755.4 and the maximum gain are obtained. Since the solution for MPS nonsense is the most satisfying solution with a high satisfaction degree, it is important to choose a blur between the minimum value and the maximum value of w *. The well-distributed value of w * belongs to a group of musicians.

6. Conclusion

The purpose of this research project was to find the most effective UOP for MPS problems that have not been identified. SMF was recently developed as a framework for the task of solving the above problems effectively. The decision-making process and its implementation will be easier if the decision maker and consultant can work with the analyst to get the best and most satisfactory results. There are two more cases to consider in future work of the running technology that is not negative and that the dynamic assets are running and not complicated. FS mathematical relationships can be developed for MPS problems to find satisfying solutions. The decision maker, researcher and practitioner can apply their knowledge and experience to get the best results.

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