

Comparative Study of Yager and Magnitude Based Ranking on TrFN with Left and Right Fuzziness and apply on Fuzzy Geometric Programming Problem

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ABSTRACT: Geometric programming problem is a powerful tool for solving some special type non-linear programming problems. It has a wide range of applications in optimization and engineering for solving some complex optimization problems. Most of the optimization techniques with geometric programming are analyzed on certain fixed unchanged environment. But real life applications are situation oriented and uncertain due to changing the different environmental effects. Fuzzy system deals with such uncertain situation in much more realistic manner. Here we try to use trapezoidal fuzzy data on geometric programming using Yager's ranking method and a new approach of magnitude derivation technique. After that we compare these two methods under different conditions of left fuzziness and right fuzziness for getting best possible result from a fuzzy geometric programming problem where the coefficients of decision variables in the objective function, the constraint coefficients, and the right-hand sides are fuzzy numbers.

KEYWORDS: Yager's ranking method, geometric programming, fuzzy number, generalized fuzzy number, trapezoidal fuzzy number, left fuzziness, right fuzziness.

I. INTRODUCTION

Geometric programming, a technique developed for solving algebraic nonlinear programming problems subject to linear or nonlinear constraints, is useful in the study of a variety of optimization problems. Its great impact has been in the area of integrated circuit design [9], [10], manufacturing system design [11] and project management. The familiar posynomial geometric programming is

$$\begin{aligned} \text{Min } f(x) &= \sum_{j=1}^{N_0} c_{0j} \prod_{i=1}^n x_i^{a_{0ij}} \\ \text{Subject to } g_k(x) &= \sum_{j=1}^{N_k} c_{kj} \prod_{i=1}^n x_i^{a_{kij}} \leq b_i \quad \text{Or} \quad \frac{1}{b_i} g_k(x) = \frac{1}{b_i} \sum_{j=1}^{N_k} c_{kj} \prod_{i=1}^n x_i^{a_{kij}} \leq 1 \end{aligned} \quad (1)$$

Where c_{0j} ($j=1, 2, \dots, N_0$) c_{kj} ($k=1, 2, \dots, m; j=1, 2, \dots, N_k$) b_i ($i=1, 2, \dots, n$)

If the primal problem is in posynomial form, then a global minimizing solution to that problem can be obtained by solving the dual maximization. The dual problem has the desirable features of being linearly constrained and having an objective function with attractive structural properties. This allows for the development of powerful solution techniques for geometric programs.

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Efficient algorithms have been developed for solving the geometric programming problems when the cost and constraint coefficients are known exactly. However, many applications of geometric programming are engineering design problems in which some of the problem parameters are estimates of actual values [2]. There are also cases that these coefficients may not be presented in a precise manner. For example, the tool life in machining economics model may fluctuate due to different machining operations and conditions. To deal quantitatively with imprecise information in making decisions, Bellman and Zadeh and Zadeh introduce the notion of fuzziness. Here we try to work on geometric programming problem where coefficients of decision variables in the objective function, the constraint coefficients, and the right-hand sides are trapezoidal fuzzy numbers. We apply the Yager's ranking index method and a new magnitude based ranking approach on trapezoidal fuzzy number under the different conditions of left fuzziness, right fuzziness and compares the results for two different ranking approaches. Here we try to explain Yager's ranking index method and magnitude based ranking approach when left fuzziness is greater, less and equal to right fuzziness and derive the conclusion accordingly from the various results of geometric programming problems.

II. PRELIMINARIES

A. Definition

A fuzzy number is a fuzzy set like $u: R \rightarrow I = [0,1]$ satisfies

1. u is upper semi-continuous.
2. $u(x) = 0$ Outside some interval $[a, b]$
3. There are real numbers a, b such that $a \leq b \leq c \leq d$
4. $u(x)$ is monotonically increasing on $[a, b]$
5. $u(x)$ is monotonically increasing on $[c, d]$
6. $u(x) = 1; b \leq x \leq c$

The membership function for fuzzy number u can be expressed

$$u(x) = \left\{ \begin{array}{ll} u_L(x), & a \leq x \leq b \\ 1, & b \leq x \leq c \\ u_R(x), & c \leq x \leq d \\ 0, & \text{otherwise} \end{array} \right\} \quad (2)$$

Where $u_L: [a, b] \rightarrow [0,1]$ and $u_R: [c, d] \rightarrow [0,1]$ are left and right membership functions of fuzzy number u .

B. Definition

An arbitrary fuzzy number is presented by an ordered pair of functions $(\underline{u}(\alpha), \bar{u}(\alpha)), 0 \leq \alpha \leq 1$, which satisfies the following requirements:

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1. $\underline{u}(\alpha)$ is a bounded left continuous non decreasing function over $[0,1]$, with respect to any α
2. $\bar{u}(\alpha)$ is a bounded left continuous non increasing function over $[0,1]$, with respect to any α
3. $\underline{u}(\alpha) \leq \bar{u}(\alpha), 0 \leq \alpha \leq 1$

C. Definition

If $\tilde{x} = (x_a, x_b, x_c, x_d)$ and $\tilde{y} = (y_a, y_b, y_c, y_d)$ are two trapezoidal fuzzy number then division of these two fuzzy numbers will be

$$\frac{\tilde{x}}{\tilde{y}} = \left(\frac{x_a}{y_d}, \frac{x_b}{y_c}, \frac{x_c}{y_b}, \frac{x_d}{y_a} \right) \tag{3}$$

D. Definition

The trapezoidal fuzzy number $u = (x_0, y_0, \delta, \beta)$ with two defuzzifier x_0, y_0 and left fuzziness $\delta > 0$ and right fuzziness $\beta > 0$ is a fuzzy set where the membership function is as

$$u(x) = \left\{ \begin{array}{ll} \frac{1}{\delta} (x - x_0 + \delta), & x_0 - \delta \leq x \leq x_0 \\ 1, & x \in [x_0, y_0] \\ \frac{1}{\beta} (y_0 - x + \beta), & y_0 \leq x \leq y_0 + \beta \\ 0, & \text{otherwise} \end{array} \right\} \tag{4}$$

And parametric form is $\underline{u}(\alpha) = x_0 - \delta + \delta\alpha, \bar{u}(\alpha) = y_0 + \beta - \beta\alpha$

III. YAGER'S RANKING METHOD FOR TRAPIZOIDAL FUZZY DATA

A special version of linear ranking method for a fuzzy data was introduced by Yager. If \tilde{u} is a fuzzy number where α cut of \tilde{u} is $[\tilde{u}^L_\alpha, \tilde{u}^U_\alpha]$ then according to Yager's Method for Ranking the ranking function is

$$R(\tilde{u}) = \frac{1}{2} \int_0^1 (u^L_\alpha + u^U_\alpha) d\alpha \tag{5}$$

For Trapezoidal fuzzy number $\tilde{u} = (x_0, y_0, \delta, \beta)$, we have $R(\tilde{u}) = \frac{2x_0 + 2y_0 - \delta + \beta}{4}$ (6)

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Proof:

According to parametric form of trapezoidal fuzzy number $u = (x_0, y_0, \delta, \beta)$ with two defuzzifier x_0, y_0 and left fuzziness $\delta > 0$ and right fuzziness $\beta > 0$, we get

$$\underline{u}(\alpha) = x_0 - \delta + \delta\alpha, \quad \bar{u}(\alpha) = y_0 + \beta - \beta\alpha$$

Now putting these two values at equation (5) we get

$$\begin{aligned} R(\tilde{u}) &= \frac{1}{2} \int_0^1 ((x_0 + y_0) + (\delta - \beta)\alpha - (\delta - \beta)) d\alpha \\ &= \frac{1}{2} \int_0^1 (x_0 - \delta + \delta\alpha + y_0 + \beta - \beta\alpha) d\alpha \\ &= \frac{1}{2} \left((x_0 + y_0) - (\delta - \beta) + \frac{(\delta - \beta)}{2} \right) \\ &= \frac{1}{4} (2x_0 + 2y_0 - 2\delta + 2\beta + \delta - \beta) \\ &= \frac{1}{4} (2x_0 + 2y_0 + \beta - \delta) \end{aligned}$$

IV. NEW APPROACH FOR RANKING METHOD FOR TRAPIZOIDAL FUZZY DATA

For any arbitrary Trapezoidal fuzzy number $\tilde{u} = (x_0, y_0, \delta, \beta)$ with parametric form $\underline{u}(\alpha) = x_0 - \delta + \delta\alpha, \bar{u}(\alpha) = y_0 + \beta - \beta\alpha$ from equation (4) we can define the magnitude of $\tilde{u} = (x_0, y_0, \delta, \beta)$ as

$$M a g (\tilde{u}) = \frac{1}{2} \left[\int_0^1 (\underline{u}(\alpha) + \bar{u}(\alpha) + x_0 + y_0) \alpha d\alpha \right] \tag{7}$$

For Trapezoidal fuzzy number $\tilde{u} = (x_0, y_0, \delta, \beta)$, we have

$$M a g (\tilde{u}) = \frac{1}{12} (6x_0 + 6y_0 + \beta - \delta) \tag{8}$$

Proof:

According to parametric form of trapezoidal fuzzy number $u = (x_0, y_0, \delta, \beta)$ with two defuzzifier x_0, y_0 and left fuzziness $\delta > 0$ and right fuzziness $\beta > 0$, we get

$$\underline{u}(\alpha) = x_0 - \delta + \delta\alpha, \quad \bar{u}(\alpha) = y_0 + \beta - \beta\alpha$$

Now putting these two values at equation (7) we get

$$\begin{aligned} M a g (\tilde{u}) &= \frac{1}{2} \left[\int_0^1 (\underline{u}(\alpha) + \bar{u}(\alpha) + x_0 + y_0) \alpha d\alpha \right] \\ &= \frac{1}{2} \left[\int_0^1 (x_0 - \delta + \delta\alpha + y_0 + \beta - \beta\alpha + x_0 + y_0) \alpha d\alpha \right] \end{aligned}$$

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$$\begin{aligned}
 &= \frac{1}{2} \left(2(x_0 + y_0) \left[\frac{\alpha^2}{2} \right]_0^1 - (\delta - \beta) \left[\frac{\alpha^2}{2} \right]_0^1 + (\delta - \beta) \left[\frac{\alpha^3}{3} \right]_0^1 \right) \\
 &= \frac{1}{2} \left((x_0 + y_0) + \frac{(\delta - \beta)}{3} - \frac{(\delta - \beta)}{2} \right) = \frac{1}{12} (6x_0 + 6y_0 + 2\delta - 2\beta - 3\delta + 3\beta) = \frac{1}{12} (6x_0 + 6y_0 + \beta - \delta)
 \end{aligned}$$

V. CONDITIONAL APPROACH OF LEFT AND RIGHT FUZZINESS ON RANKING INDEX METHODS

According to parametric form of trapezoidal fuzzy number $u = (x_0, y_0, \delta, \beta)$ with two defuzzifier x_0, y_0 and left fuzziness $\delta > 0$ and right fuzziness $\beta > 0$, using equation (6) and (8) we can get three conditions.

$$\left. \begin{aligned}
 &\frac{1}{4}(2x_0 + 2y_0 + \beta - \delta) > \frac{1}{12}(6x_0 + 6y_0 + \beta - \delta) \\
 &\frac{1}{4}(2x_0 + 2y_0 + \beta - \delta) < \frac{1}{12}(6x_0 + 6y_0 + \beta - \delta) \\
 &\frac{1}{4}(2x_0 + 2y_0 + \beta - \delta) = \frac{1}{12}(6x_0 + 6y_0 + \beta - \delta) \\
 &\text{If } \frac{1}{4}(2x_0 + 2y_0 + \beta - \delta) > \frac{1}{12}(6x_0 + 6y_0 + \beta - \delta) \\
 &\text{Then} \\
 &\frac{1}{4}(2x_0 + 2y_0 + \beta - \delta) - \frac{1}{12}(6x_0 + 6y_0 + \beta - \delta) > 0 \\
 &\frac{6x_0 + 6y_0 + 3\beta - 3\delta - 6x_0 - 6y_0 - \beta + \delta}{12} > 0 \quad \text{or} \quad \frac{2\beta - 2\delta}{12} > 0 \\
 &\beta > \delta
 \end{aligned} \right\} \tag{9}$$

Same way from other derivations we can conclude,

1. $R(\tilde{u}) > Mag(\tilde{u})$, only if $\beta > \delta$
2. $R(\tilde{u}) < Mag(\tilde{u})$, only if $\beta < \delta$
3. $R(\tilde{u}) = Mag(\tilde{u})$, only if $\beta = \delta$

VI. GENERALIZED EQUATION FOR FUZZY GEOMETRIC PROGRAMMING

Here we are taking the coefficients of objective function, constraints and right hand side of constraints as Trapezoidal fuzzy number.

$$\left. \begin{aligned}
 \text{Min } f(x) &= \sum_{j=1}^{N_0} \tilde{c}_{0j} \prod_{i=1}^n x_i^{a_{0ij}} \\
 \text{Subject to } g_k(x) &= \sum_{j=1}^{N_k} \tilde{c}_{kj} \prod_{i=1}^n x_i^{a_{kij}} \leq \tilde{b}_i \quad \text{Or} \quad \frac{1}{\tilde{b}_i} g_k(x) = \frac{1}{\tilde{b}_i} \sum_{j=1}^{N_k} \tilde{c}_{kj} \prod_{i=1}^n x_i^{a_{kij}} \leq 1 \\
 g_k(x) &= \sum_{j=1}^{N_k} \tilde{c}_{kj} \prod_{i=1}^n x_i^{a_{kij}} \leq \tilde{b}_i \quad \text{Or} \quad \frac{1}{\tilde{b}_i} g_k(x) = \frac{1}{\tilde{b}_i} \sum_{j=1}^{N_k} \tilde{c}_{kj} \prod_{i=1}^n x_i^{a_{kij}} \leq 1
 \end{aligned} \right\} \tag{10}$$

Where \tilde{c}_{0j} ($j=1,2,\dots,N_0$), \tilde{c}_{kj} ($k=1,2,\dots,m; j=1,2,\dots,N_k$), \tilde{b}_i ($i=1,2,\dots,n$) are trapezoidal fuzzy data.

To solve the Fuzzy geometric programming we need to convert the equation (10) into its dual form. So the following is Fuzzy dual geometric programming equation.

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$$\left. \begin{aligned}
 \text{Max } v(\lambda) &= \prod_{k=0}^m \prod_{j=1}^{N_k} \left(\frac{\tilde{c}_{kj}}{\lambda_{kj}} \sum_{l=1}^{N_k} \lambda_{kl} \right)^{\lambda_{kj}} \quad \text{Subject to } \sum_{j=1}^{N_0} \lambda_{0j} = 1, \sum_{k=0}^m \sum_{j=1}^{N_k} a_{kij} \lambda_{kj} = 0, \lambda_{kj} \geq 0 \\
 k &= 1, 2, \dots, m \text{ where } i = 1, 2, \dots, n; j = 1, 2, \dots, N_k;
 \end{aligned} \right\} \quad (11)$$

VII. COMPARATIVE STUDY OF YAGER'S RANKING AND MAGNITUDE BASED RANKING ON FUZZY GEOMETRIC PROGRAMMING

A. Dual form of Fuzzy geometric programming equation with Yager's approach

$$\left. \begin{aligned}
 \text{Max } v(\lambda) &= \prod_{k=0}^m \prod_{j=1}^{N_k} \left(\frac{R(\tilde{c}_{kj})}{\lambda_{kj}} \sum_{l=1}^{N_k} \lambda_{kl} \right)^{\lambda_{kj}} \quad \text{Where } R(\tilde{c}_{kj}) = \text{Yager's Ranking based value.} \\
 \text{Subject to } &\sum_{j=1}^{N_0} \lambda_{0j} = 1, \sum_{k=0}^m \sum_{j=1}^{N_k} a_{kij} \lambda_{kj} = 0, \lambda_{kj} \geq 0 \text{ where } i=1, 2, \dots, n; j=1, 2, \dots, N_k; k=1, 2, \dots, m
 \end{aligned} \right\} \quad (12)$$

B. Dual form of Fuzzy geometric programming equation with Magnitude based approach

$$\left. \begin{aligned}
 \text{Max } v(\lambda) &= \prod_{k=0}^m \prod_{j=1}^{N_k} \left(\frac{\text{Mag}(\tilde{c}_{kj})}{\lambda_{kj}} \sum_{l=1}^{N_k} \lambda_{kl} \right)^{\lambda_{kj}} \quad \text{Where } \text{Mag}(\tilde{c}_{kj}) = \text{Magnitude based value.} \\
 \text{Subject to } &\sum_{j=1}^{N_0} \lambda_{0j} = 1, \sum_{k=0}^m \sum_{j=1}^{N_k} a_{kij} \lambda_{kj} = 0, \lambda_{kj} \geq 0 \text{ where } i=1, 2, \dots, n; j=1, 2, \dots, N_k; k=1, 2, \dots, m
 \end{aligned} \right\} \quad (13)$$

Now we will explain the effect of left fuzziness and right fuzziness on the N_0^{th} (from objective function of primal problem) and N_{nm}^{th} (m^{th} value of n^{th} constrain of primal problem) value of objective function in dual form with Yager's approach (equation (12)) and Magnitude based approach (equation (13)).

C. For Yager's approach $R(\tilde{c}_{0N_0}) = \frac{1}{4}(2x_{0N_0} + 2y_{0N_0} + \beta_{N_0} - \delta_{N_0})$ and $R(\tilde{c}_{nmN_m}) = \frac{1}{4}(2x_{mN_m} + 2y_{mN_m} + \beta_{N_m} - \delta_{N_m})$

Considering only these two values in dual form of geometric programming

$$\text{Max}_{\text{Yager}} (v_{N_0}, v_{N_m}) = \left[\frac{1}{4} \frac{(2x_{0N_0} + 2y_{0N_0} + \beta_{N_0} - \delta_{N_0})}{\lambda_{0N}} (\lambda_{01} + \lambda_{02} + \lambda_{03} + \dots + \lambda_{0N}) \right]^{\lambda_{0N}} \cdot \left[\frac{1}{4} \frac{(2x_{mN_m} + 2y_{mN_m} + \beta_{N_m} - \delta_{N_m})}{\lambda_{mN_m}} (\lambda_{m1} + \lambda_{m2} + \lambda_{m3} + \dots + \lambda_{mN_m}) \right]^{\lambda_{mN_m}} \quad (14)$$

D. For Magnitude based approach

$\text{Mag}(\tilde{c}_{0N_0}) = \frac{1}{12}(6x_{0N_0} + 6y_{0N_0} + \beta_{N_0} - \delta_{N_0})$ And $\text{Mag}(\tilde{c}_{nmN_m}) = \frac{1}{12}(6x_{mN_m} + 6y_{mN_m} + \beta_{N_m} - \delta_{N_m})$

Considering only these two values in dual form of geometric programming

$$\text{Max}_{\text{Mag}} (v_{N_0}, v_{N_m}) = \left[\frac{1}{12} \frac{(6x_{0N_0} + 6y_{0N_0} + \beta_{N_0} - \delta_{N_0})}{\lambda_{0N}} (\lambda_{01} + \lambda_{02} + \lambda_{03} + \dots + \lambda_{0N}) \right]^{\lambda_{0N}} \cdot \left[\frac{1}{12} \frac{(6x_{mN_m} + 6y_{mN_m} + \beta_{N_m} - \delta_{N_m})}{\lambda_{mN_m}} (\lambda_{m1} + \lambda_{m2} + \lambda_{m3} + \dots + \lambda_{mN_m}) \right]^{\lambda_{mN_m}} \quad (15)$$

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$$\begin{aligned}
 \frac{Max_{yager}(v_{N_0}, v_{N_m})}{Max_{Magnitude_based}(v_{N_0}, v_{N_m})} &= \frac{\left[\frac{1}{4} \left(\frac{2x_{0N_0} + 2y_{0N_0} + \beta_{N_0} - \delta_{N_0}}{\lambda_{0N}} \right) (\lambda_{01} + \lambda_{02} + \lambda_{03} + \dots + \lambda_{0N}) \right]^{\lambda_{0N}} \left[\frac{1}{4} \left(\frac{2x_{mN_m} + 2y_{mN_m} + \beta_{N_m} - \delta_{N_m}}{\lambda_{nN_m}} \right) (\lambda_{n1_m} + \lambda_{n2_m} + \lambda_{n3_m} + \dots + \lambda_{nN_m}) \right]^{\lambda_{nN_m}}}{\left[\frac{1}{12} \left(\frac{6x_{0N_0} + 6y_{0N_0} + \beta_{N_0} - \delta_{N_0}}{\lambda_{0N}} \right) (\lambda_{01} + \lambda_{02} + \lambda_{03} + \dots + \lambda_{0N}) \right]^{\lambda_{0N}} \left[\frac{1}{12} \left(\frac{6x_{mN_m} + 6y_{mN_m} + \beta_{N_m} - \delta_{N_m}}{\lambda_{nN_m}} \right) (\lambda_{n1_m} + \lambda_{n2_m} + \lambda_{n3_m} + \dots + \lambda_{nN_m}) \right]^{\lambda_{nN_m}}} \\
 \frac{Max_{yager}(v_{N_0}, v_{N_m})}{Max_{Magnitude_based}(v_{N_0}, v_{N_m})} &= \frac{(3)^{\lambda_{0N}} \cdot (2x_{0N_0} + 2y_{0N_0} + \beta_{N_0} - \delta_{N_0})^{\lambda_{0N}} \cdot (3)^{\lambda_{nN_m}} \cdot (2x_{mN_m} + 2y_{mN_m} + \beta_{N_m} - \delta_{N_m})^{\lambda_{nN_m}}}{(6x_{0N_0} + 6y_{0N_0} + \beta_{N_0} - \delta_{N_0})^{\lambda_{0N}} \cdot (6x_{mN_m} + 6y_{mN_m} + \beta_{N_m} - \delta_{N_m})^{\lambda_{nN_m}}} \\
 \frac{Max_{yager}(v_{N_0}, v_{N_m})}{Max_{Magnitude_based}(v_{N_0}, v_{N_m})} &= \frac{(6x_{0N_0} + 6y_{0N_0} + 3\beta_{N_0} - 3\delta_{N_0})^{\lambda_{0N}}}{(6x_{0N_0} + 6y_{0N_0} + \beta_{N_0} - \delta_{N_0})^{\lambda_{0N}}} \cdot \frac{(6x_{mN_m} + 6y_{mN_m} + 3\beta_{N_m} - 3\delta_{N_m})^{\lambda_{nN_m}}}{(6x_{mN_m} + 6y_{mN_m} + \beta_{N_m} - \delta_{N_m})^{\lambda_{nN_m}}} \quad (16)
 \end{aligned}$$

VIII. CONDITION ANALYSIS

A. If right fuzziness is greater than left fuzziness ($\beta > \delta$) then

$$\frac{Max_{yager}(v_{N_0}, v_{N_m})}{Max_{Magnitude_based}(v_{N_0}, v_{N_m})} > 1 \text{ Or } Max_{yager}(v_{N_0}, v_{N_m}) > Max_{Magnitude_based}(v_{N_0}, v_{N_m})$$

So, for primal problem, $Min_{yager}(v_{N_0}, v_{N_m}) > Min_{Magnitude_based}(v_{N_0}, v_{N_m})$

It means, Magnitude based ranking will give better result than Yager's approach.

B. If right fuzziness less than left fuzziness ($\beta < \delta$) then

$$\frac{Max_{yager}(v_{N_0}, v_{N_m})}{Max_{Magnitude_based}(v_{N_0}, v_{N_m})} < 1 \text{ Or } Max_{yager}(v_{N_0}, v_{N_m}) < Max_{Magnitude_based}(v_{N_0}, v_{N_m})$$

So, for primal problem, $Min_{yager}(v_{N_0}, v_{N_m}) < Min_{Magnitude_based}(v_{N_0}, v_{N_m})$

It means, Yager's ranking will give better result than Magnitude based ranking approach.

C. If right fuzziness less than left fuzziness ($\beta = \delta$) then

$$\frac{Max_{yager}(v_{N_0}, v_{N_m})}{Max_{Magnitude_based}(v_{N_0}, v_{N_m})} = 1 \text{ Or } Max_{yager}(v_{N_0}, v_{N_m}) = Max_{Magnitude_based}(v_{N_0}, v_{N_m})$$

So, for primal problem, $Min_{yager}(v_{N_0}, v_{N_m}) = Min_{Magnitude_based}(v_{N_0}, v_{N_m})$

It means, Yager's ranking and Magnitude based ranking approach will give same result.

IX. CONCLUSION

Depending on the condition analysis, it is clear that, the conclusive decision regarding the better approach of Yager and Magnitude based ranking, is purely dependent on value of right and left fuzziness. For greater value of right fuzziness, Magnitude based ranking will give better result and for greater value of left fuzziness, Yager based ranking will give better result. For same value of left and right fuzziness, two ranking will give equal performance.

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BIOGRAPHY



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