EKSAKTA
Journal of Sciences and Data Analysis

E-ISSN: 2720-9326
P-ISSN: 2716-0459
DOI: 10.20885/EKSAKTA.vol3.iss1.art5

Research Article

Multi Criteria Decision Making Using Normalized 3 – Polar ELECTRE I and Fuzzy 3 – Polar *Dombi Arithmatic AOs* (Case Study of Determining Manufacture Location)

Ricky Haryanto[1],Sugiyarto Surono[1,*]

[1] Mathematics Department, Faculty of Applied Science and Technology Universitas Ahmad Dahlan, Yogyakarta, Indonesia

[*] *Corresponding author: sugiyarto@math.uad.ac.id*

Received: 3 February 2022; Accepted: 18 March 2022; Published: 19 March 2022

Abstract: The m-Polar fuzzy set is a set that not only overcomes data ambiguity, but can also handle multi-polar, multi-attribute, and multi-criteria information. The m-Polar fuzzy set is useful in describing uncertainty in multi-attribute decision-making. One of the techniques used in decision-making is the ELECTRE I method. The ELECTRE I method plays a role in conducting pairwise comparisons between alternatives given by the decision-maker, where alternatives, criteria, and weights are given by the decision-maker. Furthermore, the ranking results from the ELECTRE I method will be compared with the mF Dombi Weighted Averaging (m-FDWA) aggregation operator with the help of the arithmetic operator. The purpose of this study was to compare the ranking results of the mF ELECTRE I, and the normalized and non-normalized m-FDWA arithmatic methods. The data used is secondary data related to site selection for global manufacturing with 20 alternative countries (country) and 8 criteria. The results showed that the best alternative to the normalized mF ELECTRE I and m-FDWA methods was country 14. While the m-FDWA arithmetic method without normalization resulted in country 3 as the best alternative. The effectiveness test was applied to m-FDWA arithmetic method, both normalized and without normalization to test the validity of the model so that it can be seen that normalization does not affect the validity of the model.

Keywords: Effectiveness test, Dombi arithmatic Aos, ELECTRE I , m – Polar, Normalization

Introduction

Multi Criteria Decision Making (MCDM) is a decision-making method that determines the best alternative based on criteria or several rules. The technic of MCDM is related with designing and evaluating decision structure and planning problem that involving several criteria [1]. MCDM has widely used to solve problem in several topics like in economy, business, technology information, and medical health. The solving of MCDM case can be done by considering problem representation, *fuzzy* set evaluation, choosing optimal alternative, data source, and type of data [2].

One of the method in MCDM, especially MADM is ELECTRE method [2]. ELECTRE was introduced by Benayon, et. al [3] to show the option between several alternatives by double-comparing those alternatives through *outranking* relation [4]. It then explained further by Roy [5] and defined as ELECTRE I. The fundamental concept of this method is determining the concordance and discordance of the set that each represents the positive and negative of every alternative so that it resulted in the best alternative [6,7].

ELECTRE I method is known as the appropriate *outranking* approach to be used in all type of information and desired to choose a group of preferred alternative but didn't produce option that exceed outranking alternative [1,8,9]. Aside of ELECTRE I, there are other ELECTRE methods such as

ELECTRE II, ELECTRE III, ELECTRE IV, ELECTRE IS, and ELECTRE TRI that are another type from ELECTRE method [1,6], 9,10]. The positive of ELECTRE method is it has less input to solve a problem with moderately high number of alternative and criteria [10].

MADM *fuzzy* method is proposed to solve the problem that involving *fuzzy* data. Bellman dan Zadeh [11] are the first individuals that connect the *fuzzy* set theory with decision-making problem. Zadeh introduced *fuzzy* set that is able to handle ambiguous information, in which the membership degree falls between the interval of [0,1] [12]. In general, ordinary *fuzzy* set is limited. Several extension and generalization of *fuzzy* set has been introduced [13], where it includes *Hesitant Fuzzy Sets* (HFSs) [14], *Bipolar Fuzzy Sets* (BFSs) [15], dan *m - Polar Fuzzy Sets* (*mF sets*) [16].

In 2014, *m*-Polar set theory was introduced by Chen [16] where it was defined as generalization of bipolar *fuzzy* set. The set of *m*-Polar on X set is a mapping of $\mu : X \rightarrow [0,1]$. The concept of *m*-Polar information is happening because the real-world data comes from a lot of characters and understanding. The set of *m* - Polar shows a better representation from unclear set of data, that results in significantly better study in the parameter of equality, incompleteness, and data relation. [13].

Multipolar information holds an important role in many situations. Knowing the fact that the set of *m*-Polar has efficient power in handling unclear data that shows up in real-world problem, the need of aggregation operators (AOs) in combining information is critical [17–18]. AOs have important role in solving MCDM problem and combining data into one shape of data (single form) [19–21].

Several prior studies done by Hatami – Marbini [22] uses ELECTRE method to do a ranking in evaluation of health safety in Hazardous Waste Recycling (HWR) facility. Neha Waseem did a new approach in ELECTRE I method by using *m*-Polar *fuzzy* set to register the criteria and the alternative which later will be compared using *fuzzy* ELECTRE I [23]. Muhammad Akram [20] did a study with an approach of using Dombi aggregation operator in decision-making under *m*-Polar fuzzy set.

This study will explain about the comparison of decision making using ELECTRE I method and both normalized and unnormalized method of *m*-Polar *Dombi Weighted Averaging* (*m*-FDWA) *Arithmetic* AOs which will result in the rank of alternative and criteria given by decision maker. Then, by using *m*-Polar *fuzzy* set will do alternative input and criteria from decision maker. The result of this study is to show the best and optimal alternative which will be chosen alternative.

Methods

Triangular Membership Function

Membership function can be represented in several ways, one of it is function approach. The representation of triangular curve will be used to change crisp data into *fuzzy* data. In principle, the triangular curve is a combination of 2 linear as shown in Figure 1.

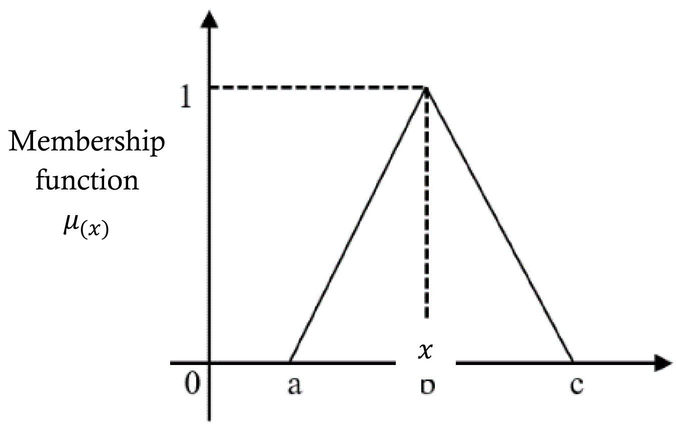

Figure 1. Triangular membership function.

Membership function:

$$\mu_{(x)} = \begin{cases} 0; x < a \text{ or } x > c \\ \dfrac{(x-a)}{(b-a)}; a \le x \le b \\ \dfrac{(c-x)}{(c-b)}; b \le x \le c \end{cases} \quad (1)$$

*m*F ELECTRE I

Prior to solving MCDM problem, the explanation of *m*-Polar ELECTRE I method is needed. If $A = \{a_1, a_2, a_3, \dots, a_r\}$ is a set of alternative and $C = \{c_1, c_2, c_3, \dots, c_k\}$ is the set of criteria, the initial step of *m*-Polar ELECTRE I *fuzzy* method is to form a decision matrix filled with alternative that is suitable with the criteria, in which the decision matrix are symbolized by $D = (d_{ij})$, with:

$$D = (d_{ij}) = (d_{ij}^1, d_{ij}^2, d_{ij}^3, \dots, d_{ij}^m)$$

After the decision matrix is formed, the next step is to determine the weight of decision maker by complying to normality condition, that is,

$$\sum_{j=1}^{k} w_j = 1$$

The formed decision matrix then have to went through normalization using equation as follows:

$$r_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d^2{}_{ij}}}; \; i = 1, 2, \dots, m \quad (2)$$

After normalization, the continuing step is the normalized decision matrix being multiplied with the weight so that it resulted in *m*-Polar *fuzzy* decision matrix weighted by $Y = (y_{ij})$, in which

$$Y = (y_{ij}) = (y_{ij}^1, y_{ij}^2, y_{ij}^3, \dots, y_{ij}^m),$$

with $y_{ij} = w_j z_{ij}$. The next step is to have *concordance fuzzy m*-Polar set formed which is defined as:

$$F_{pq} = \{1 \le j \le k : v_{pj} \ge v_{qj}, p \ne q; p, q = 1,2, \dots, r\},$$

and *discordance fuzzy m*-Polar set is defined as

$$G_{pq} = \{1 \le j \le k : v_{pj} \le v_{qj}, p \ne q; p, q = 1,2, \dots, r\},$$

with $v_{ij} = y_{ij}^1 + y_{ij}^2 + y_{ij}^3 + \dots, + y_{ij}^m$, in which the index of *concordance fuzzy m* – Polar f_{pq} are calculated using equation as follows:

$$f_{pq} = \sum_{j \in F_{pq}} w_j \quad (1)$$

while for the calculation of index of *discordance fuzzy m* – Polar (4)

$$g_{pq} : g_{pq} = \frac{\max_{j \in G_{pq}} \{|y_{aj} - y_{bj}|\}}{\max_j \{|y_{aj} - y_{bj}|\}}$$

for all of p, q. So the matrix of *concordance fuzzy* $m-$ Polar $\boldsymbol{F}$ and the matrix of *discordance fuzzy* $m-$ Polar $\boldsymbol{G}$ can be formed as follows:

$$\boldsymbol{F}=\begin{pmatrix} - & f_{12} & f_{13} & \cdots & f_{1r} \\ f_{21} & - & f_{23} & \cdots & f_{2r} \\ f_{31} & f_{32} & - & \cdots & f_{3r} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ f_{r1} & f_{r2} & f_{r3} & \cdots & - \end{pmatrix}, \quad \boldsymbol{G}=\begin{pmatrix} - & g_{12} & g_{13} & \cdots & g_{1r} \\ g_{21} & - & g_{23} & \cdots & g_{2r} \\ g_{31} & g_{32} & - & \cdots & g_{3r} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ g_{r1} & g_{r2} & g_{r3} & \cdots & - \end{pmatrix}$$

The next step is to calculate the level of *concordance fuzzy* $m-$ Polar $\bar{f}$ and *discordance fuzzy* $m-$ Polar $\bar{g}$ which is defined as the average of the index by using equation below:

$$\bar{f}=\frac{1}{r(r-1)}\sum_{\substack{p=1\\p\neq q}}^{r}\sum_{\substack{q=1\\q\neq p}}^{r} f_{pq} \tag{5}$$

$$\bar{g}=\frac{1}{r(r-1)}\sum_{\substack{p=1\\p\neq q}}^{r}\sum_{\substack{q=1\\q\neq p}}^{r} g_{pq} \tag{6}$$

so the dominant matrix of both *concordance fuzzy* $m-$ Polar and *discordance fuzzy* $m-$ Polar can be formed in matrix showed below:

$$\boldsymbol{H}=\begin{pmatrix} - & h_{12} & h_{13} & \cdots & h_{1r} \\ h_{21} & - & h_{23} & \cdots & h_{2r} \\ h_{31} & h_{32} & - & \cdots & h_{3r} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ h_{r1} & h_{r2} & h_{r3} & \cdots & - \end{pmatrix}, \quad \boldsymbol{L}=\begin{pmatrix} - & l_{12} & l_{13} & \cdots & l_{1r} \\ l_{21} & - & l_{23} & \cdots & l_{2r} \\ l_{31} & l_{32} & - & \cdots & l_{3r} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ l_{r1} & l_{r2} & l_{r3} & \cdots & - \end{pmatrix}$$

where $h_{pq}=\begin{cases}1, f_{pq}\geq \bar{f}\\ 0, f_{pq}<\bar{f}\end{cases}$ and $l_{pq}=\begin{cases}1, g_{pq}\geq \bar{g}\\ 0, g_{pq}<\bar{g}\end{cases}$.

peer to peer multiplication of entry $\boldsymbol{H}$ and $\boldsymbol{L}$ are done to make the aggregation dominant matrix $\boldsymbol{M}$ showed as follows:

$$M=\begin{pmatrix} - & m_{12} & m_{13} & \cdots & m_{1r} \\ m_{21} & - & m_{23} & \cdots & m_{2r} \\ m_{31} & m_{32} & - & \cdots & m_{3r} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ m_{r1} & m_{r2} & m_{r3} & \cdots & - \end{pmatrix}$$

The last step is to rank the alternatives based on outranking value from matrix $\boldsymbol{M}$, where there is trending side (represented in trending graph) from entry x_a to x_b if and only if the value of $m_{ab}=1$. This resulted in three cases, that are:

- There is trending side from x_a to x_b, which means x_a is more preferred than x_b.
- There is trending side from x_a to x_b and x_b to x_a, which means there is no difference between the two.
- No side in between x_a to x_b, or unable to be compared.

Dombi Aggregation Operator

On the principle, the *sum* of Dombi operation and Dombi product are $t-$ norm and $t-$ conorm, which are defined as follows.

$$D^*(p,q) = p \oplus q = 1 - \frac{1}{1 + \left\{\left(\frac{p}{1-p}\right)^k + \left(\frac{q}{1-q}\right)^k\right\}^{1/k}}$$

$$D(p,q) = p \otimes q = 1 - \frac{1}{1 + \left\{\left(\frac{1-p}{p}\right)^k + \left(\frac{1-q}{q}\right)^k\right\}^{1/k}}$$

where k ≥ 1 and a, b ∈ [0, 1] [20]. Dombi operation is given with Dombi *t*-conorm and Dombi *t-norm* and also aggregation operator (AOs) m – Polar Dombi *Arithmetic.* If $\hat{C}_1 = (p_1 \circ C_1, \dots, p_m \circ C_1)$, $\hat{C}_2 = (p_1 \circ C_2, \dots, p_m \circ C_2)$, and $\hat{C} = (p_1 \circ C, \dots, p_m \circ C)$ are *m*FNS, so the Dombi operation for *m*FNS:

$$\hat{C}_1 \oplus \hat{C}_2 = \left(1 - \frac{1}{1 + \left\{\left(\frac{p_1 \circ C_1}{1 - p_1 \circ C_1}\right)^k + \left(\frac{p_1 \circ C_2}{1 - p_1 \circ C_2}\right)^k\right\}^{\frac{1}{k}}}, \dots, 1 - \frac{1}{1 + \left\{\left(\frac{p_m \circ C_1}{1 - p_m \circ C_1}\right)^k + \left(\frac{p_m \circ C_2}{1 - p_m \circ C_2}\right)^k\right\}^{\frac{1}{k}}}\right) \quad (7)$$

$$\hat{C}_1 \otimes \hat{C}_2 = \left(\frac{1}{1 + \left\{\left(\frac{1 - p_1 \circ C_1}{p_1 \circ C_1}\right)^k + \left(\frac{1 - p_1 \circ C_2}{p_1 \circ C_2}\right)^k\right\}^{\frac{1}{k}}}, \dots, \frac{1}{1 + \left\{\left(\frac{1 - p_m \circ C_1}{p_m \circ C_1}\right)^k + \left(\frac{1 - p_m \circ C_2}{p_m \circ C_2}\right)^k\right\}^{\frac{1}{k}}}\right)$$

$$B\hat{C} = \left(1 - \frac{1}{1 + \left\{B\left(\frac{p_1 \circ C}{1 - p_1 \circ C}\right)^k\right\}^{\frac{1}{k}}}, \dots, 1 - \frac{1}{1 + \left\{B\left(\frac{p_m \circ C}{1 - p_m \circ C}\right)^k\right\}^{\frac{1}{k}}}\right)$$

$$(\hat{C})^B = \left(1 - \frac{1}{1 + \left\{B\left(\frac{1 - p_1 \circ C_1}{p_1 \circ C_1}\right)^k\right\}^{\frac{1}{k}}}, \dots, 1 - \frac{1}{1 + \left\{B\left(\frac{1 - p_1 \circ C_1}{p_1 \circ C_1}\right)^k\right\}^{\frac{1}{k}}}\right)$$

where $k > 0$.

Results and Discussions

On this research, there is an addition of step that is normalizing decision matrix on *m*-FDWA *Arithmetic* AOs which then will be compared with both *m*-FDWA *Arithmetic* AOs with no normalization method and *m*F ELECTRE I method to produce the best alternative of determining global manufacture location.

The data used is a secondary data extracted from online site (*https://dc.uwm.edu/cgi/viewcontent.cgi? article=1238&context=etd*). The alternative of the criteria is inputted in the form om multicriteria information so the set that is used is *fuzzy m* – Polar set, in which every membership degree represents sub criteria. In determining manufacture location, the developer, or the contractor in this case, need to consider several things related to determining the location of construction [24]. The specialists on the subject are already being asked as decision maker to determine the alternative and criteria of choosing the location. They will evaluate twenty alternatives or candidates $A_i\ (i = 1, 2, \dots, 20)$, with criteria such as C_1: *Cost*, C_2: *Labor*, C_3: *Infrastructure*, C_4: *Market*, C_5: *Other Locations*, C_6: *Economic*, C_7: *Quality of Life*, and C_8: *Political*. The weight of the criteria is also applied by decision maker in $W = (0.07, 0.19, 0.06, 0.17, 0.12, 0.19, 0.08, 0.12)$ which is obtained from random values using Python software. Data from decision makers are shown in Table 1.

Table 1. Decision matrix

	C1	C2	...	C8
A1	(32.32, 61.31, 67.15)	(3, 20.87, 36.14)	...	(19, 5, 4)
A2	(32.92, 32.04, 55.43)	(1, 17.13, 60.33)	...	(22, 2, 2)
⋮	⋮	⋮	⋱	⋮
A20	(37.26, 63.81, 46.11)	(4, 14.43, 75.91)	...	(30, 10, 17)

*m*F ELECTRE I

Based on **Error! Reference source not found.**, the initial step of *m*F ELECTRE I method approach in solving the problem of determining global manufacture location is to do a *fuzzification* on crisp data showed in Table 1 using triangular function so it will be changed into *fuzzy*. The *fuzzification* result is shown in Table 2, in which those data is the data of 3 *polar fuzzy numbers* where every value represents the value in sub criteria.

Table 2. Polar decision matrix

	C1	C2	...	C8
A1	(0, 0, 0)	(0.66667, 0.57191, 0)	...	(0, 0.5556,)
A2	(0, 0, 0.61783)	(0, 0.86382, 0.04791)	...	(0.111, 0, 0)
⋮	⋮	⋮	⋱	⋮
A20	(0.85734, 0, 0)	(0.81818, 0.55993, 0)	...	(0.52941, 0, 0)

The normalization of decision matrix is done next in accordance with equation (2), with the result written as follows:

$$\boldsymbol{N} = \begin{pmatrix} 0, 0, 0 & 0.35351, 0.3374, 0 & \cdots & 0, 0.26575, 0 \\ 0, 0, 0.30201 & 0, 0.50961, 0.02906 & \cdots & 0.06149, 0, 0 \\ 0.0475, 0.24084, 0.22399 & 0, 0.03694, 0 & \cdots & 0, 0.47834, 0 \\ 0, 0, 0.48837 & 0, 0, 0 & \cdots & 0, 0, 0.23021 \\ \vdots & \vdots & \ddots & \vdots \\ 0.37423, 0, 0 & 0.43385, 0.33033, 0 & \cdots & 0.29298, 0, 0 \end{pmatrix}$$

After that, the normalized decision matrix is multiplied with each weight of the criteria.

$$\boldsymbol{Y} = \begin{pmatrix} 0,0,0 & 0.04271, 0.04076, 0 & \cdots & 0, 0.03189, 0 \\ 0,0,0.0199 & 0, 0.06157, 0.00351 & \cdots & 0.00738, 0, 0 \\ 0.00313, 0.01587, 0.01476 & 0, 0.00446, 0 & \cdots & 0, 0.0574, 0 \\ 0,0,0.03217 & 0,0,0 & \cdots & 0,0,0.02763 \\ \vdots & \vdots & \ddots & \vdots \\ 0.02465, 0, 0 & 0.05242, 0.03991, 0 & \cdots & 0.03516, 0, 0 \end{pmatrix}$$

After the weighed normalized decision matrix is obtained, the next step is to form the index of *concordance* and *discordance,* each are shown in Table 3 and Table 4.

Table 3. Concordance index

j	1	2	...	20
F_{1j}	-	{2, 3, 5, 6, 8}	...	{3, 4, 5, 7}
F_{2j}	{1, 4, 7}	-	...	{4, 7}
⋮	⋮	⋮	⋱	⋮
F_{20j}	{1, 2, 6, 8}	{1, 2, 3, 5, 6 ,8}	...	-

Table 4. Discordance index

j	1	2	3	...	20
G_{1j}	-	{1, 4, 7}	{3, 4, 7, 8}	...	{1, 2, 6, 8}
G_{2j}	{2, 3, 5, 6, 8}	-	{1, 3, 7, 8}	...	{1, 2, 3, 5, 6, 8}
⋮	⋮	⋮	⋮	⋱	⋮
G_{20j}	{1, 2, 6, 8}	{4, 7}	{2, 4, 5, 6}	...	–

From index of *concordance* and *discordance*, the 3F (3 polar) *concordance* and matrix 3F (3 polar) *discordance* are obtained which each are being calculated with the formula (3) and (4), it is shown in matrix ***F*** and ***G*** below.

$$\boldsymbol{F} = \begin{pmatrix} - & 0.57113 & 0.64593 & 0.66268 & \cdots & 0.61666 \\ 0.42887 & - & 0.39226 & 0.48381 & \cdots & 0.36299 \\ 0.35407 & 0.60774 & - & 0.66503 & \cdots & 0.54421 \\ 0.33732 & 0.51619 & 0.33497 & - & \cdots & 0.63437 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0.38334 & 0.63701 & 0.45579 & 0.5076 & \cdots & - \end{pmatrix}$$

$$\boldsymbol{G} = \begin{pmatrix} - & 0.61655 & 0.81228 & 1 & \cdots & 0.36797 \\ 1 & - & 0.87618 & 0.34289 & \cdots & 0.58151 \\ 1 & 1 & - & 1 & \cdots & 0.64383 \\ 0.83078 & 1 & 0.73449 & - & \cdots & 0.32525 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & 1 & \cdots & - \end{pmatrix}$$

The continuing step is to determine the level of 3F *concordance* and level 3F *discordance* which will be used as threshold parameter in determining the dominant matrix of *concordance* and *discordance*. Based on equation (5) and (6), the level value of 3F *concordance* $\bar{f} = 0.5055$ and level 3F *discordance* $\bar{g} = 0.85734$. So, the dominant matrix of *concordance* and *discordance* can be written as follows:

$$\boldsymbol{H} = \begin{pmatrix} - & 1 & 1 & 1 & \cdots & 1 \\ 0 & - & 0 & 0 & \cdots & 0 \\ 0 & 1 & - & 1 & \cdots & 1 \\ 0 & 1 & 0 & - & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & 1 & \cdots & - \end{pmatrix}, \quad \boldsymbol{L} = \begin{pmatrix} - & 1 & 1 & 0 & \cdots & 1 \\ 0 & - & 0 & 1 & \cdots & 1 \\ 0 & 0 & - & 0 & \cdots & 1 \\ 1 & 0 & 1 & - & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & - \end{pmatrix}$$

After the dominant matrix of *concordance* and *discordance* are obtained, the next step is to determine the aggregate dominant matrix of 3F which obtained from peer to peer multiplication of entry $\boldsymbol{H}$ and $\boldsymbol{L}$, so the aggregate dominant matrix of $\boldsymbol{M}$ is showed by matrix below:

$$\boldsymbol{M} = \begin{pmatrix} - & 1 & 1 & 0 & \cdots & 1 \\ 0 & - & 0 & 0 & \cdots & 0 \\ 0 & 0 & - & 0 & \cdots & 1 \\ 0 & 0 & 0 & - & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & - \end{pmatrix}$$

The last step is to represent the result of aggregate dominant matrix by using outranking relation into trending graph which is shown in Figure 2.

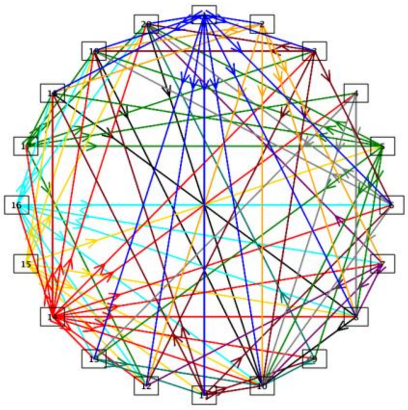

Figure 2. Outranking relation of determining global manufacture location.

From figure 2, the red color shows A14 which dominates other alternatives as evidenced by the edge of the graph that comes out of the A14 vertex and leads to the top of the vertex in the graph above, this means that A14 has superior criteria compared to other alternatives. It can be concluded that A14 or country 14 is the best location for global manufacturing.

Normalized *m*FDWA Method

By using normalized matrix data shown in equation (8), the next step is to calculate the value of $\hat{c}_i$ in determining the location of global manufacturing A_i with $k = 3$ in accordance with equation (7), so that the result is obtained as follows

$$\hat{c}_1 = (0.39920, 0.26538, 0.39158)$$

$$\hat{c}_2 = (0.45089, 0.42574, 0.14883)$$

$$\vdots$$

$$\hat{c}_{20} = (0.30490, 0.32205, 0.21619)$$

The next step is to decide the score value of $S(\hat{s}_i)$ from 3FNs $\hat{s}_i$, which is the average value of $\hat{c}_i$, so that the result is obtained as follows

$$S(\hat{c}_1) = 0.35205$$

$$S(\hat{c}_2) = 0.34182$$

$$\vdots$$

$$S(\hat{c}_{20}) = 0.28105$$

So, according to the score value of $S(\hat{s}_i)$, $(i = 1, 2, \dots)$. Based on Figure 2 it is obtained where $A_{14} > A_{15} > A_{16} > A_1 > A_8 > A_3 > A_2 > A_{11} > A_5 > A_7 > A_{20} > A_{17} > A_9 > A_{18} > A_4 > A_{19} > A_6 > A_{10} > A_{13} > A_{12}$. Because A_{14} has the highest score, it can be concluded that A_{14} or *country* 14 is the best alternative for the location of global manufacturing.

Effectiveness Test Using Normalized *M*fdwa Method

To ensure the validity of both, normalized and non-normalized, *m*FDWA algorithm method, the criteria test developed by Wang [25] is needed. Criteria test are done to change the value on the least optimal alternative, in this case alternative A_{12} and A_{10}. The exchange value of alternative A_{12} and A_{10} each are shown in Table 5 and Table 6. The calculation then are being redone using *m*FDWA method but there was no different in the rank result where A_{14} still have the highest score and are the best alternatives. Since there was no difference detected in the rank of optimal alternative after going through effectiveness test, it can be concluded that the two methods of *m*FDWA are valid.

Table 5. The Change of Membership Value on A_{12} using the method of normalized *mF Dombi Arithmatic Aos*

Alternative	Cost			Labor			Infrastructure			Market		
	L	M	TC	ET	UR	ML	T	U	QRT	PC	S	PPM
A'_{12}	0.172	0	0.0826	0	0.5112	0.1735	0	0	0.1	0.105	0	0

Alternative	Other Locations			Economic			Quality of life			Politics		
	PSP	PPC	PC	CSD	IR	I	SL	HC	ES	SP	CPP	GATFI
A'_{12}	0.004	0.0324	0	0.2113	0.1356	0.267	0	0	0	0	0	0.0196

Table 6. The Change of Membership Value on A_{10} using the method of *mF Dombi Arithmatic AOs* with no normalization

Alternative	Cost			Labor			Infrastructure			Market		
	L	M	TC	ET	UR	ML	T	U	QRT	PC	S	PPM
A'_{10}	0.2677	0.5125	0	0	0.2507	0.4521	0.4332	0	0	0	0	0.3809

Alternative	Other Locations			Economic			Quality Of Life			Politics		
	PSP	PPC	PC	CSD	IR	I	SL	HC	ES	SP	CPP	GATFI
A'_{10}	0	0	0	0	0.4603	0.7295	0.5341	0	0	0.4306	0.3201	0

Conclusion

It can be concluded from this research that *m*-Polar *fuzzy* set has a role in managing multicriteria information given by decision maker, which is information in the form of criteria in determining the location of global manufacturing with 8 criteria with each is made of 3 sub criteria. According to the calculation, the ranking of the methods used in this research (3-Polar ELECTRE I *fuzzy* method and normalized 3-Polar *Dombi Arithmetic AOs fuzzy* method) showed the same alternative. By using effectiveness test, it then revealed that adding normalization step in *mF Dombi Arithmatic AOs* didn't affect the method validity. Even, by having a normalization, the triangular *fuzzy* calculation is helped in the case of in which the result is undefined value or 1/0.

The next research can focus on the other ELECTRE method in wider perspective in considering the suitability level and unsuitability of information given. Other type of *fuzzification* are also open to be explained further in decision-making method with the output as *m*-Polar *fuzzy* set, *hesitant fuzzy, fuzzy* intuition, etc.

References

[1] Shumaiza, M. Akram, and A. N. Al-Kenani, Multiple-attribute decision making ELECTRE II method under bipolar fuzzy model, Algorithms 12(11) (2019) 1–24, doi: 10.3390/a12110226.
[2] S. H. Kusumadewi, Fuzzy Multi-Attribute Decision Making (Fuzzy MADM), Yogyakarta: Graha Ilmu, 2006.
[3] R. Benayoun, B. Roy, and B. Sussmann, Manuel de réference du programme electre, Note synthèse, Form. n.25, Dir. Sci. SEMA, Paris, 1966.
[4] H. Dinçer, Ü. Hacıoğlu, and S. Yüksel, Managerial and Market-Based Appraisal of Agriculture Banking Using ANP and ELECTRE Method, Manag. Organ. Stud. 3(3) (2016), doi: 10.5430/mos.v3n3p29.
[5] B. Roy, The outranking approach and the foundations of electre methods, Theory Decis., 1991, doi: 10.1007/BF00134132.
[6] T. Romario, V. Gunawan, and J. Endro, Implementation of the ELECTRE Method for Determining the Location of Evacuation of Web-based Tsunami Disaster, Int. J. Comput. Appl. 180(52) (2018) 25–31, doi: 10.5120/ijca2018917362.
[7] M. Gökhan Yücel and A. Görener, Decision making for company acquisition by ELECTRE method, Int. J. Supply Chain Manag. 5(1) (2016) 75–83.
[8] M. Akram, H. Garg, and K. Zahid, Extensions of electre-i and topsis methods for group decision-making under complex pythagorean fuzzy environment, Iran. J. Fuzzy Syst. 17(5) (2020) 147–164, doi: 10.22111/ijfs.2020.5522.
[9] X. Yu, S. Zhang, X. Liao, and X. Qi, ELECTRE methods in prioritized MCDM environment, Inf. Sci. (Ny)., 2018, doi: 10.1016/j.ins.2017.09.061.
[10] R. Baki, "Personnel selection through Fuzzy ELECTRE I method, 2019.
[11] R. E. Bellman and L. A. Zadeh, Decision-Making in a Fuzzy Environment, Manage. Sci., 1970, doi: 10.1287/mnsc.17.4.b141.
[12] L. A. Zadeh, Fuzzy sets, Inf. Control, 1965, doi: 10.1016/S0019-9958(65)90241-X.
[13] A. Adeel, M. Akram, I. Ahmed, and K. Nazar, Novel m-polar fuzzy linguistic ELECTRE-I method for group decision-making, Symmetry (Basel)., 11(4) (2019 1–26, doi: 10.3390/sym11040471.
[14] R. M. Rodriguez, L. Martinez, and F. Herrera, Hesitant fuzzy linguistic term sets for decision making, IEEE Trans. Fuzzy Syst. 20(1) (2012) 109–119, doi: 10.1109/TFUZZ.2011.2170076.
[15] W. R. Zhang and L. Zhang, YinYang bipolar logic and bipolar fuzzy logic, Inf. Sci. (Ny). 165(3-4) (2004) 265–287, 2004, doi: 10.1016/j.ins.2003.05.010.
[16] J. Chen et al., m-Polar Fuzzy Sets An Extension of Bipolar Fuzzy Sets.pdf., 2014.
[17] M. Lin, W. Xu, Z. Lin, and R. Chen, Determine OWA operator weights using kernel density estimation, Econ. Res. Istraz. 33(1) (2020) 1441–1464, doi: 10.1080/1331677X.2020.1748509.
[18] C. Jana, M. Pal, and J. qiang Wang, Bipolar fuzzy Dombi aggregation operators and its application in multiple-attribute decision-making process, J. Ambient Intell. Humaniz. Comput. 10(9) (2018) 3533–3549, doi: 10.1007/s12652-018-1076-9.

[19] F. Hamacher and A. Operators, SS symmetry Fuzzy Hamacher Aggregation Operators, (2019) 1–33, doi: 10.3390/sym11121498.
[20] M. Akram, N. Yaqoob, G. Ali, and W. Chammam, Extensions of Dombi Aggregation Operators for Decision Making under m -Polar Fuzzy Information, 2020 (2020).
[21] X. He, Group decision making based on Dombi operators and its application to personnel evaluation, 2019, doi: 10.1002/int.22118.
[22] A. Hatami-Marbini, M. Tavana, M. Moradi, and F. Kangi, A fuzzy group Electre method for safety and health assessment in hazardous waste recycling facilities, Saf. Sci., 51(1) (2013) 414–426, doi: 10.1016/j.ssci.2012.08.015.
[23] M. Akram, N. Waseem, and P. Liu, Novel Approach in Decision Making with m–Polar Fuzzy ELECTRE-I, Int. J. Fuzzy Syst. 21(4) (2019) 1117–1129, doi: 10.1007/s40815-019-00608-y.
[24] A. H. Kalantari, Facility Location Selection for Global Manufacturing, Univ. Wisconsin-Milwaukee, 81(19) (2013) 87.
[25] X. Wang and E. Triantaphyllou, Ranking irregularities when evaluating alternatives by using some ELECTRE methods, Omega, 36(1) (2008) 45–63, doi: 10.1016/j.omega.2005.12.003.