International Journal of Science and Technology
(STECH)
Bahir Dar- Ethiopia
Vol. 5 (2), S/No12, October, 2016: 91-102
ISSN: 2225-8590 (Print) ISSN 2227-5452 (Online)
DOI: http://dx.doi.org/10.4314/stech.v5i2.7

A Review of Intuitionistic Fuzzy Topsis for Supplier Selection

Omorogbe, Dickson E. A., Ph.D.
Institute of Education
Ekehuan Campus
University of Benin, Benin City, Nigeria
E-mail: erhaativie.omorogbe@uniben.edu
Mobile Phone: +2348033312830

Abstract

This paper presented a review of intuitionistic fuzzy TOPSIS (Technique for Order Preference by Similarity to the Ideal Solution) for supplier selection in literature and identified gaps and lapses associated with the existing method. We also proposed new research frontiers.

Key Words: intuitionistic fuzzy TOPSIS, supplier selection, metric functions

Introduction

Many established approaches for the evaluation and selection of suppliers have been considered in literature. According to Omosigho and Omorogbe (2015), "Ho et al (2010) did a review of some of the methods suggested for solving the supplier selection problem. The methods reviewed include: Data envelopment analysis (DEA), Mathematical programming, Analytic hierarchy process (AHP), Case-based reasoning (CBR), Fuzzy set theory, Simple multi-attribute rating technique (SMART), Genetic algorithm (GA)". They also considered hybrid methods combining some of the methods and their variations. Ho et al. (2010) reviewed 78 articles and literature of the multi-criteria decision making approaches for supplier evaluation and selection from 2000 to 2008. They, Ho et al (2010) also considered the methods that have been used in addressing MCDM problem during this period. Ho et al. (2010) work not only provides evidence that multi-criteria decision making approaches are better than the traditional cost-based approach, but also aids the researchers and decision makers (DM) in applying the approaches effectively. According to Ho et al. (2010) supplier evaluation and selection have been studied extensively. Various decision making approaches have been proposed to tackle the problem. In contemporary supply chain management, the performance of potential suppliers is evaluated against multiple criteria rather than considering a single factor –cost (Ho et al., 2010). There are other attributes or factors that can be taken into consideration in choosing a supplier other than cost (Izadikhah, 2012). Some of the attributes used in the evaluation and selection of suppliers are: 1. Price/cost, 2. Quality, 3. Delivery leadtime, 4. Manufacturing capacity, 5. Service, 6. Management, 7. Technology, 8. Research and development, 9. Finance, 10. Fexibility, 11. Reputation, 12. Relationship, 13. Risk, 14. Safety and enviroment and their related attributes (Ho et al, 2010). Other attributes in literature are: 15. Reliability, 16. Performance history/experience (Amiri et al, 2011), 17. Policy of warranty and legal claims, 18. Willingness to cooperate, 19. Organizational behaviour and adaptation to purchaser's needs (Izadekhah, 2012). Soeini et al. (2012) also reviewed some articles on the supplier selection problem. These authors however ignored intuitionistic fuzzy TOPSIS (Technique for Order Preference by Similarity to the Ideal Solution). Amindoust et al. (2012) gave some information on intuitionistic fuzzy TOPSIS but ignored the problem associated with the use of several metric for the same problem Omosigho and Omorogbe (2015). This paper re-examined the approach for supplier selection based on intuitionistic fuzzy TOPSIS.The paper identified gaps associated with the use of this technique and proposed a new research frontier.

Fuzzy Set (FS)

The fuzzy set theory is used to solve the rigorous theory of approximation and vagueness based on generalization of standard set theory to fuzzy set or numbers (Carlsson and Fuller, 1996). Fuzzy set and fuzzy logic are powerful mathematical tools for addressing uncertain system in the absence of complete and precise information. However, fuzzy set theory only provides approximate solution. The classical set theory is built on the fundamental concept of set which is either a member or not a member. A sharp, crisp and unambiguous distinction exists between a member and non-member for any well-defined set of entities in this theory. There is a precise and clear boundary to indicate if any entity belongs to the set or not. But many real life problems cannot be described or handled by classical set theory.

A fuzzy set is an extension of crisp set. Crisp set only allows full membership. While fuzzy set allows both full membership and partial membership. In other words, an element may partially belong to a fuzzy set. The theory uses value ranges from 0-1 for showing membership of the objects in a fuzzy set. Complete non-membership is denoted as 0, and complete membership as 1. Values between 0 and 1 represent intermediate degree of membership (Jajimoggala et al., 2011 & Seifbarghy et al., 2011). The fuzzy system only provides approximate solution and not exact solution because of it amenability to human reasoning process.

Intuitionistic Fuzzy Sets (IFSs)

Intuitionistic Fuzzy Set (IFSs) extends the membership function of fuzzy set by including both non-membership and hesitation functions into the model.

Intuitionistic Fuzzy Set A in a finite set U can be written as:

$U= \{u_1, u_2, \dots u_n\}$ is the universe of discourse.

$A= \{u_i, \mu_A(u_i), \nu_A(u_i), \tau_A(u_i)\}$ is an intuitionistic fuzzy subset

$B= \{u_i, \mu_B(u_i), \nu_B(u_i), \tau_B(u_i)\}$ is also intuitionistic fuzzy subset

$(i= 1,2,\dots n)$

Where

$\mu_A(u_i)$ is a membership function or degree

$\nu_A(u_i)$ is non membership function or degree

$\tau_A(u_i)$ is the hesitation degree

But $0 \leq \mu_A (u_i) \leq 1$ (1)

$0 \leq \nu_A (u_i) \leq 1$ (2)

$0 \leq \mu_A (u_i) + \nu_A (u_i) \leq 1$ (3)

$\mu_A (u_i) + \nu_A (u_i) + \tau_A (u_i) = 1$ (4)

Then $\tau_A (u_i) = 1 - \mu_A (u_i) - \nu_A (u_i)$ (5)

Clearly $0 \leq \tau_A (u_i) \leq 1$ (6)

Some of the authors that use intuitionistic fuzzy set in their studies are Husain et al. (2012), Boran et al. (2011), Chai and Liu (2010), Li et al. (2007), Shan, 2012 and Izadekhah (2012).

Intuitionistic Fuzzy TOPSIS

According to Wu and Liu (2011), the TOPSIS method was developed in 1981 by Hwang and Yoon. Generally, the method is based on the concept of minimum distance from the positive ideal solution and maximum distance from the negative ideal solution. The Negative Ideal Solution (NIS) is the solution that maximizes the cost factor and minimizes the benefit factors, while the Positive Ideal Solution (PIS) is the solution that minimizes the cost factor and maximizes the benefit factors. One of the limitation of TOPSIS method is the problem associated with the use of more than one functions in intuitionistic fuzzy environment. Some of the authors that applied the TOPSIS method are Wu and Liu (2011), Elanchezhian et al. (2010), Ashrafzadel et al. (2012), Kabir (2012). Boran et al. (2009), Wen et al. (2013)

The algorithm for intuitionistic fuzzy TOPSIS as used by Boran et al. (2009) is stated as follows:

Step 1: Determine the Weights of Decision Makers

Step 2. Construct Aggregate Intuitionistic Fuzzy Decision Matrix based on the Opinions of DMs

Step 3. Determine the Weight of the Criteria

Step 4. Construct Final (Aggregated Weighted) Intuitionistic Fuzzy Decision Matrix

Step 5. Obtain the positive ideal solution (PIS) and negative ideal solution (NIS)

Step 6: Construct the separation measures (distance from PIS and distance from NIS) for each supplier. The computation of separation measure is given in eqs. (8), (9), (10) and (11) are commonly used in literature.

Step 7: Calculate the closeness coefficients for each supplier. The calculation for closeness coefficient is given below.

$CC = H- / H- + H+$, where $0 \leq CC \leq 1$. (7)

Where eq. (7) is applicable to the distance functions and their variations for calculating the similarity measures or closeness coefficients of the suppliers.

According to Omosigho and Omorogbe (2015) to trasform qualitative attributes in the evaluation and selection of suppliers, several versions of TOPSIS have been introduced in literature. In particular, in intuitionistic fuzzy TOPSIS, the weights of criteria, the decision matrix (rating of the alternative suppliers) are initially obtained in linguistic terms. The linguistic terms are transformed to intuitionistic fuzzy numbers (Amindoust et al., 2012b, Boran et al., 2009 and Izadikhah, 2012). There are different versions of linguistic variables. In the literature, a five-point scale, or a seven-point scale or a ten-point scale for the same concept can be found in (Boran et al., 2009 and Izadikhah, 2012, Saghafian and Hejazi, 2005, Wen et al. 2013). Details of how to manipulate the linguistic variables to obtain the final intuitionistic fuzzy decision matrix, intuitionistic fuzzy positive ideal solution (PIS) and intuitionistic fuzzy negative ideal solution (NIS) are however the same (Amindoust et al., 2012b, Boran et al., 2009 and Izadikhah, 2012) and references therein. The PIS is a matrix containing the best ratings for all criteria and the NIS is a matrix containing the worst ratings for criteria. The idea of the TOPSIS is that the selected supplier should be closest to the PIS and farthest from the NIS. To achieve this, the distances (S_+ and S_-) of each supplier from the PIS and NIS respectively are calculated based on a chosen metric function and used to calculate the closeness coefficient. The closeness coefficient is given by S_- |(S_+ + S_-) (Omosigho & Omorogbe, 2014).

Metric Functions for Intuitionistic Fuzzy Sets

In this section, we give a cursory review of metric functions for intuitionistic fuzzy sets. There are many metric functions used for the calculation of distances between fuzzy sets. Table 1 shows some metric functions considered for intuitionistic fuzzy sets in recent literature.

Table 1: Metric functions for calculating distances between intuitionistic fuzzy sets

Metric functions (Name and Mathematical Definitions)	Authors
a. Hamming distance *H(A,B)* $H(A,B)=\frac{1}{2}\sum_{i=1}^{n}[\mid \mu_A(x_i)-\mu_B(x_i)\mid + \mid \nu_A(x_i)-\nu_B(x_i)\mid + \mid \tau_A(x_i)-\tau_B(x_i)\mid]$ (8)	Szmidt and Kacprzyk (2000), Grzegorzewwski(2004). Yang and Chiclana (2009),
b. Normalized Hamming distance *H(A,B)* $H(A,B)=\frac{1}{2n}\sum_{i=1}^{n}[\mid \mu_A(x_i)-\mu_B(x_i)\mid + \mid \nu_A(x_i)-\nu_B(x_i)\mid + \mid \tau_A(x_i)-\tau_B(x_i)\mid]$ (9)	Szmidt and Kacprzyk (2000), Grzegorzewwski (2004). Yang and Chiclana (2009).
c. Euclidean distance *E(A, B)* $E(A,B)=(\frac{1}{2}\sum_{i=1}^{n}[(\mu_A(x_i)-\mu_B(x_i))^2+(\nu_A(x_i)-\nu_B(x_i))^2+(\tau_A(x_i)-\tau_B(x_i))^2])^{0.5}$ (10)	Szmidt and Kacprzyk (2000), Grzegorzewwski (2004). Yang and Chiclana (2009),
d. Normalized Euclidean distance *E(A, B)* $E(A,B)=(\frac{1}{2n}\sum_{i=1}^{n}[(\mu_A(x_i)-\mu_B(x_i))^2+(\nu_A(x_i)-\nu_B(x_i))^2+(\tau_A(x_i)-\tau_B(x_i))^2])^{0.5}$ (11)	Szmidt and Kacprzyk (2000), Grzegorzewwski (2004). Yang and Chiclana (2009)

e. Hausdorff distance $d_H(A,B) = \max\{(\lvert\mu_A(x_i) - \mu_B(x_i)\rvert, \lvert\nu_A(x_i) - \nu_B(x_i)\rvert\}$ (12)	Grzegorzewwski (2004)
f. L_P distance $d_P(A,B) = \left(\lvert\mu_A(x_i) - \mu_B(x_i)\rvert^P + \lvert\nu_A(x_i) - \nu_B(x_i)\rvert^P\right)^{1/P}, \quad p \geq 1$ (13)	Hung and Yang (2007)
g. Spherical distance *S(A,B)* $S(A,B) = \frac{2}{\pi}\sum_{i=1}^{n} ar\cos(\sqrt{\mu_A(x_i)\mu_B(x_i)} + \sqrt{\nu_A(x_i)\nu_B(x_i)} + \sqrt{\tau_A(x_i)\tau_B(x_i)})$ (14)	Yang and Chiclana (2009)

Szmidt and Kacprzyk (2000) extended the Hamming and Euclidean metric functions and their variations in eqs.(8) – (11) to 3D intuitionistic fuzzy set by incorporating third parameter ( ) $_i \tau$ x (intuitionistic fuzzy index) into the metric function. Yang and Chiclana (2009) introduced the spherical distance in eq.(2.26) and suggested that it may be more convenient to measure the distances in a 3D intuitionistic fuzzy set. According to Yang and Chiclana (2009) the semantic difference between intuitionistic variables is not shown by linear (commonly used) distances. Therefore, a non-linear representation of the distances between two intuitionistic fuzzy sets would benefit the representation of intuitionistic fuzzy sets. Yang and Chiclana (2009) proposed the Spherical distance to provides a convenient non-linear measure of the distance between two intuitionistic sets.

The Hausdorff and $_P L$ distances in eqs. (13) and (14) are only in 2D spaces. But, the 3D spaces of Hamming and Euclidean and Spherical distances as defined in Yang and Chiclana (2009) are in Table 1. Other non-linear metrics in literature such as: X_2LMNN (Large Margin Nearest Neighbours), GB-LMNN (Gradient Boosting- Large Margin Nearest Neighbours), and Hadamard distance. These non-linear metrics are defined in some papers such as (Kakavandi and Amini, 2011, Kedem et. al, 2012, Grzegorzewwski, 2004). To the best of our knowledge they have not been implemented for supplier selection problems. It will be interesting to see how their application will affect supplier selection problems.

Commonly Used Metric Functions in Intuitionistic Fuzzy TOPSIS

The commonly used metric functions for the calculation of the separation measure in TOPSIS are Euclidean metric and the Hamming metric and their variations. According to Szmidt and Kacprzyk (2000) the presence of ½ before the summation notation in eqs. (8) to (11) is attributed to the fact that the distance between intuitionistic fuzzy variables is twice that of the fuzzy counterparts. Omosigho and Omorogbe (2014) showed example of authors that applied the indicated metric functions in intuitionistic fuzzy TOPSIS for supplier selection. Jorge et al [10] applied the Malahanobis metric. Table 1 in Omosigho and Omorogbe (2015) shows the aforementioned commonly used metric functions in intuitionistic fuzzy TOPSIS and authors that applied them in their work.

Nevertheless, the application of more than one of these metric functions for the same supplier selection problem produces contradictory ranking of the suppliers (Chen and Tsao, 2008). Indeed, Chen and Tsao (2008) performed a comparative study of TOPSIS technique using different metrics. The metrics considered were two different definitions of the Hamming metric and three different definitions of the Euclidean metric. In their study, they concluded that "in a decision problem, the interval-valued fuzzy TOPSIS methods using the different distance definitions may yield distinct preference orders when the number of alternatives is greater than 5. Second, the best alternative suggested by the interval-valued fuzzy TOPSIS methods using different distance definitions might be contradictory in some degree. As the number of alternatives increases, there is greater chance that the most preferred alternatives based on distinct distances will differ substantially." Hence it is important to examine the metric functions adopted in the application of intuitionistic fuzzy TOPSIS for the supplier selection problem.

The conclusion of Chen and Tsao (2008) is not surprising based on the following argument. Szmidt and Kacprzyk (2000) demonstrated that the representation of two intuitionistic fuzzy subsets affects the distance between them. Further, Yang and Chiclana (2009) noted that the Hamming and Euclidean metrics are based on the linear representation of intuitionistic fuzzy sets. This is in sharp contrast to semantic differences which is not linear in nature. Zadeh (1975) had earlier examined the concept of linguistic variables and their transformation to fuzzy numbers. Essentially, the argument proposed by Zadeh (1975) shows that fuzzy numbers representing linguistic variables are not linear. He used the example of "young" and presented a non-linear graph to show the transformation of age in years to fuzzy numbers in the interval [0,1], (Figure 1.1, Zadeh, 1975, P. 202). Yang and Chiclana (2009) observed that the use of "distances based on the linear representation of intuitionistic fuzzy sets might not seem to be the most appropriate ones. In such cases, nonlinear distances between intuitionistic fuzzy sets may be more adequate to capture the semantic difference." Further, Yang and Chiclana (2009) concluded that there are cases where the semantic difference is significant but linear metric (Hamming and Euclidean) will not reflect the difference. Therefore, they proposed that nonlinear metric may be more appropriate in capturing the semantic difference reflected in intuitionistic fuzzy subsets and they suggested that spherical metric should be used to compute the distance between intuitionistic fuzzy numbers. Omosigho and Omorogbe (2015) used the spherical distance in intuitionistic fuzzy TOPSIS for supplier selection and proposed the use more than one metric functions including spherical metric for the implementation of TOPSIS for supplier selection involving linguistics variables transformed into intuitionistic fuzzy numbers. This method helps to portray the deficiency of the existing method where only one distance function is adopted in TOPSIS. However, when more than one distance funtions are used in the method contradictory ranking of suppliers may be obtained. Providing a method for resolving the contradictory ranking of suppliers when more than one distance function is adopted in TOPSIS is the research agenda proposed in this paper. The application of other non-linear metrics such as: X2LMNN (Large Margin Nearest Neighbour**s**), **GB** – LMNN (Gradient Boosting - Large Margin Nearest Neighbour**s**), Hausdorff distance and Hadamard distance. These non-linear metrics are defined in some papers such as (Kakavandi and Amini, 2011, Kedem et. al, 2012, Grzegorzewwski, 2004). To the best of our knowledge they have not been implemented for supplier selection problems. It will be interesting to see how their application will affect supplier selection problems.

Proposed Research Frontiers

This paper proposed the following research frontiers to bridge the gaps in the existing method in literature:

- The problem of contradictory recommendation in the ranking of suppliers when more than one metric functions are used in intuitionistic fuzzy TOPSIS. A robust method to find a way out of the contradictory recommendation of the distance functions with respect to the ranking of suppliers is proposed as a research frontier in the existing method.
- The application of other non-linear metrics such as: X2LMNN, **GB** – LMNN, Hausdorff distance and Hadamard distance. (Kakavandi and Amini, 2011, Kedem et. al, 2012, Grzegorzewwski, 2004). To the best of my knowledge they

have not been implemented for supplier selection problems. It will be interesting to see how their application will affect supplier selection problems.

Conclusion

Intuitionistic fuzzy TOPSIS is an established method for supplier selection. This paper provided a review of the method and proposed areas of future research frontiers. Developing a method to handle the contradictory ranking of supplier when more than one metric functions are adopted will be worthwhile and invaluably enhance the supplier selection process. The application of other non-linear metric functions identified in this paper will also be a welcome development to supplier selection process.

References

Amindoust, A., Ahmed, S., & Saghafinia, A. (2012). A taxonomy and review on supplier selection methods under uncertainty. *International Journal of Information Technology and Business Management, Vol.7* No.1, 33-43.

Amiri, M., Ayazi, S. A, Olfat, L. & Moradi, J. S. (2011). Group Decision Making Process for Supplier Selection with VIKOR under Fuzzy Circumstances. Case Study: Iranian Car Parts Supplier. *International Bulletin of Business Administration, 10* pp. 62-75.

Ashrafzadeh, M., Rafiei, F. M., Isfahani, N. M., & Zare, Z. (2012). Application of Fuzzy TOPSIS method for the selection of warehose location: A case study. *Interdisciplinary Journal of Contemporary Research in Business* 3(9), 655-671.

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy sets and systems* 20, 87-96.

Boran, F E (2011). An integrated intuitionistic fuzzy multi criteria decision making method for facility location selection. *Mathematical and Computational Applications,* Vol. 16, No. 2, pp. 487-496.

Boran, F. E, Genc, S., Kurt, M. & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Systems with Applications 36*, 11363–11368.

Carlsson, C. & Fuller, R. (1996). Fuzzy multiple criteria decision making: Recent developments. *Fuzzy sets and systems* 78, 139-153.

Chai, J. & Liu. J. N. K. (2010). A novel multi-criteria group decision making approach with Intuitionistic Fuzzy SIR method. *World Automation Congress.*

Chen Ting-Yu, Tsao Chueh-Yung (2008). The interval-valued fuzzy TOPSIS method and experimental analysis. *Fuzzy Sets and Systems 159*, 1410 – 1428.

Elanchezhian, C., Ramnath, B.V., & Kesavani R., (2010). Vendor Evaluation Using Multi-criteria Decision Making Techniques. *International Journal of Computer Applications* 5(9), 4-9.

Grzegorzewski, P. (2004). Distances between intuitionistic fuzzy sets and/or interval-valued fuzzy sets based on the hausdorff metric. *Fuzzy Sets and systems i48,* 319-328.

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-Criteria Decision Making Approaches for Supplier Evaluation and Selection: A Literature Review" *European Journal of Operational Research* 202 (1), 16-24.

Hung, W. L. & Yang, M. S. (2007). Similarity measures of intuitionistic fuzzy sets based on l_p metric. *International Journal of approximate Reasoning 46*, 120-136.

Husain, S, Ahmad, Y & Alam, M. A (2012). A study on the role of intuitionalistic fuzzy set in decision making problems. *International Journal of Computer Applications* 48, (19) 888-894.

Hwang, C. L. & Yoon, K. (1981). Multiple attribute decision making: Methods and Applications. *Springer-Verlag*, New York.

Izadikhah, M. (2012). Group decision making process for supplier selection with topsis method under interval-valued intuitionistic fuzzy numbers. *Advances in Fuzzy System*, 1-14.

Jahanshahloo, G. R., Lotfi, F. H., Davoodi, A. R. (2009). Extension of TOPSIS for decision-making problems with interval data: Interval efficiency. *Mathematical and Computer Modeling* 49 1137-1142.

Jajimoggala, S., Rao, V.V. & Beela, S. K. (2011). Supplier evaluation using fuzzy analytical network process and Fuzzy TOPSIS" *Jordan Journal of Mechanical and Industrial Engineering* 5(6), 543-551.

Jorge, L., García, A., Gabriel, I. M., & Lázaro, R. P. (2009). Improvement of TOPSIS technique through integration of Malahanobis distance: A case study. *Proceedings of the 14th Annual International Conference on Industrial Engineering Theory, Applications and Practice.* Anaheim, California October 18-21, 2009.

Kabir, G. (2012). Third party logistic service provider selection using Fuzzy AHP and TOPSIS methods. *International Journal for Quality Research* 6(1), 71-79.

Kakavandi, B. A. & Amini, M (2011). Non-linear ergodic theorems in complete non-positve curvature metric spaces. *Bulletin of the Iranian Mathematical Society* 37(3), 11-20.

Kedem, D., Tyree, S., Weinberger, K. Q., Sha, F., & Lanckriet, G. (2012). Non-linear metric learning. *Advances in Neural Information Processing System 25*, 1-9.

Li, Y., Olson, D. L. & Qin, Z (2007). Similarity measures between Intuitionistic Fuzzy (vague) sets: A comparative analysis. *Pattern Recognition Letters 28,* 278-285.

Omosigho, S. E. & Omorogbe, D. E. A (2015). Supplier selection using different metric funtions. *Yugoslav Journal of Operations Research,* DOI: 10.2298/YJOR130706028O

Onut, S., & Efendigil, T. (2010). A theoretical model design for ERP software selection process approach. *Journal of Intelligence and Fuzzy Systems* 21, 365-378.

Seifbarghy, M., Gilkalayeh, A. P., & Alidoost, M., (2011). A comprehensive fuzzy multiobjective supplier selection model underprice brakes and using interval matrices. *Journal of Industrial and System Engineering,* 4(4), 224-244.

Shan, L. (2012). Research on green logistic service provider selection based on intuitionistic language fuzzy entropy. *Journal of Computers* 7(2), 540-546.

Sharma, H. K. (2012). A fuzzy logic multi-criteria decision approach for vendor selection manufacturing system. *International Journal of Modern Engineering Research (IJMER)* 2(6), 4189 – 4194.

Shemshadi, A., Toreihi, M., Shirazi, H. & Tarokh, M. J. (2011). Supplier selection based on supplier risk: An ANP and fuzzy TOPSIS approach. *The Journal of Mathematics and Computer Science,* Vol. 2 No.1, 111-121.

Soeini, R. A et al (2012). Supplier selection based on multiple criteria. *International Journal on New Computer Architectures and Their Applications* (IJNCAA) 2(1): 258-273.

Szmidt, E. & Kacprzyk, J. (2000). Distances between intuitionistic fuzzy sets. *Fuzzy Sets and Systems* 114, 505-518.

Tzeng, Gwo-Hshiung & Huang, Jih-Jeng (2011). Multiple Attribute Decision Making Methods and Applications. London: CRC Press Taylor & Francis Group.

Wen, L, Wang, R. & Zhao, W. (2013). Supplier selection based on intuitionistic fuzzy sets group decision making. *Research Journal of Applied Sciences, Engineering and Technology* 5(3): 950-956.

Wu, Feng-Yi & Chuang, Chung-Chu (2013).The optimal relationship between buyer and seller obtained using TOPSIS method. *Journal of Advanced Management Science,* Vol. 1, No. 1, March 2013.

Wu, M., & Liu, Z. (2011). The supplier selection application based on two method: VIKOR algorithm with entropy methods and Fuzzy TOPSIS with vague sets method. *International Journal of Management Science and Engineering Management.* 6(2), 110-116.

Xu, Z. (2007). Intuitionistic fuzzy aggregation operators. *IEEE Transaction on Fuzzy systems.Vol.15* No. 6, 1179-1187.

Yang, Y. & Chiclana, F. (2009). Intuitionistic Fuzzy Sets: Spherical Representation and Distances. *International Journal of Intelligent Systems, Vol.* 24, 399–420.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning-I. *Information Sciences* 8, 199-249.