A New Integrated Approach of Linear Goal Programming and Fuzzy TOPSIS for Technology Selection

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Abstract: Selection of technologies is one of the most challenging decision making areas the management of a company encounters. It is difficult to clarify the right technology alternatives because the number of technologies is increasing and the technologies are becoming more and more complex. The purpose of this paper is applying a new integrated method to technology selection. Proposed approach is based on Linear Goal Programming and Fuzzy TOPSIS methods. Linear Goal Programming method is used in determining the weights of the criteria by decision makers and then rankings of technologies are determined by fuzzy TOPSIS method. A numerical example demonstrates the application of the proposed method.

[Ahmad Jafarnejad Chaghooshi, Saiedeh Sadat Ahangari, Mohsen Moradi-Moghadam, Maryam Sadat Fagheyi. **A New Integrated Approach of Linear Goal Programming and Fuzzy TOPSIS for Technology Selection.** *N Y Sci J* 2013;6(6):58-63]. (ISSN: 1554-0200). http://www.sciencepub.net/newyork. 10

Keywords: Technology selection, Linear Goal Programming, Fuzzy set and TOPSIS.

1. Introduction

Selection of technologies is one of the most challenging decision making areas the management of a company encounters. It is difficult to clarify the right technology alternatives because the number of technologies is increasing and the technologies are becoming more and more complex. However, right technologies could create significant competitive advantages for a company in a complex business environment. The aim of technology selection is to obtain new know-how, components, and systems which will help the company to make more competitive products and services and more effective processes, or create completely new solutions (FarzipoorSaen, 2006).The rest of the paper is organized as follows: The following section presents a concise treatment of the basic concepts of fuzzy set theory. Section 3 presents the methodology of Linear Goal Programming and Fuzzy TOPSIS. The application of the proposed framework to technology selection is addressed in Section 4. Finally, conclusions are provided in Section 5.

2. Fuzzy sets and Fuzzy Numbers

Fuzzy set theory, which was introduced by Zadeh (1965) to deal with problems in which a source of vagueness is involved, has been utilized for incorporating imprecise data into the decision framework. A fuzzy set $\tilde{A}$ can be defined mathematically by a membership function $\mu_{\tilde{A}}(X)$, which assigns each element x in the universe of discourse X a real number in the interval [0,1]. A triangular fuzzy number $\tilde{A}$ can be defined by a triplet (a, b, c) as illustrated in Fig 1.

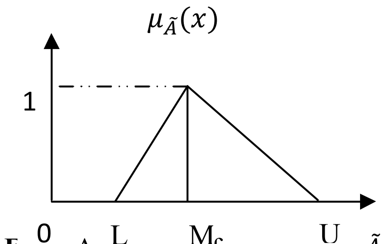

Fig. 1. A triangular fuzzy number $\tilde{A}$

The membership function $\mu_{\tilde{A}}(X)$ is defined as

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a}{b-a} & a \le x \le b \\ \frac{x-c}{b-c} & b \le x \le c \\ 0 & otherwise \end{cases} \quad (1)$$

Basic arithmetic operations on triangular fuzzy numbers $A_1 = (a_1,b_1,c_1)$, where $a_1 \le b_1 \le c_1$, and $A_2 = (a_2,b_2,c_2)$, where $a_2 \le b_2 \le c_2$,can be shown as follows:

Addition: $A_1 \oplus A_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$ (2)

Subtraction: $A_1 \ominus A_2 = (a_1 - c_2, b_1 - b_2, c_1 - a_2)$ (3)

Multiplication: if k is a scalar

$$k \otimes A_1 = \begin{cases} (ka_1, kb_1, kc_1), & k > 0 \\ (kc_1, kb_1, ka_1), & k < 0 \end{cases}$$

$$A_1 \otimes A_2 \approx (a_1a_2, b_1b_2, c_1c_2), \text{ if } a_1 \ge 0, a_2 \ge 0 \quad (4)$$

Division: $A_1 \oslash A_2 \approx (\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2})$, if $a_1 \geq 0$, $a_2 \geq 0$ (5)

Although multiplication and division operations on triangular fuzzy numbers do not necessarily yield a triangular fuzzy number, triangular fuzzy number approximations can be used for many practical applications (Kaufmann& Gupta, 1988). Triangular fuzzy numbers are appropriate for quantifying the vague information about most decision problems including personnel selection (e.g. rating for creativity, personality, leadership, etc.). The primary reason for using triangular fuzzy numbers can be stated as their intuitive and computational-efficient representation (Karsak, 2002). A linguistic variable is defined as a variable whose values are not numbers, but words or sentences in natural or artificial language. The concept of a linguistic variable appears as a useful means for providing approximate characterization of phenomena that are too complex or ill-defined to be described in conventional quantitative terms (Zadeh, 1975).

3. Research Methodology

In this paper, the weights of each criterion are calculated using of Linear Goal Programming. After that, Fuzzy TOPSIS is utilized to rank the alternatives. Finally, we select the best technology based on these results.

3.1. The Linear Goal Programming Method

Wang et al (2008) explained the Linear Goal Programming Model. In this paper, we obtain the weights of criteria based on their method. The LPG method explained as follow (Wang et al, 2008):

Consider a fuzzy pairwise comparison matrix:

$$\begin{bmatrix} (1,1,1) & (l_{12},m_{12},u_{12}) & \cdots & (l_{1n},m_{1n},u_{1n}) \\ (l_{21},m_{21},u_{21}) & (1,1,1) & \cdots & (l_{2n},m_{2n},u_{2n}) \\ \vdots & \vdots & \cdots & \vdots \\ (l_{n1},m_{n1},u_{n1}) & (l_{n2},m_{n2},u_{n2}) & \cdots & (1,1,1) \end{bmatrix} \quad (6)$$

where $l_{ij} = 1/u_{ji}$, $m_{ij} = 1/m_{ji}$ and u_{ij}, $= 1/l_{ji}$ for all i, j = 1,. . .,n;$i \neq j$ i. The above fuzzy comparison matrix can be split into three crisp nonnegative matrices:

$$\begin{bmatrix} 1 & l_{12} & \cdots & l_{1n} \\ l_{12} & 1 & \cdots & l_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ l_{n1} & l_{1n} & \cdots & 1 \end{bmatrix} \quad \begin{bmatrix} 1 & m_{12} & \cdots & m_{1n} \\ m_{12} & 1 & \cdots & m_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ m_{n1} & m_{1n} & \cdots & 1 \end{bmatrix} \quad \begin{bmatrix} 1 & u_{12} & \cdots & u_{1n} \\ u_{12} & 1 & \cdots & u_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ u_{n1} & u_{1n} & \cdots & 1 \end{bmatrix} \quad (7)$$

where $\widetilde{A} = (A_L, A_M, A_U)$. Note that A_L and A_U are no longer reciprocal matrices. For the fuzzy comparison matrix $\widetilde{A}$, there should exist a normalized fuzzy weight vector, $\widetilde{W}\left((W_1^L, W_1^M, W_1^U), \ldots, (W_n^L, W_n^M, W_n^U)\right)$ which is close to $\widetilde{A}$ in the sense that $\widetilde{A} = (l_{ij}, m_{ij}, u_{ij}) \approx \frac{(w_i^l, w_i^m, w_i^u)}{(w_j^l, w_j^m, w_j^u)}$ for all $i, j = 1, \ldots, n; j \neq i$. According to Wang et al (2006), the fuzzy weight vector $\widetilde{W}$ is normalized if and only if

$$\sum_{i=1}^{n} w_i^U - \max_j\left(w_j^U - w_j^L\right) \geq 1, \quad (8)$$
$$\sum_{i=1}^{n} w_i^L - \max_j\left(w_j^U - w_j^L\right) \leq 1, \quad (9)$$
$$\sum_{i=1}^{n} w_i^M = 1, \quad (10)$$

which can be equivalently rewritten as

$$W_i^L + \sum_{j=1, j\neq i}^{n} W_j^U \geq 1, \quad i = 1, \ldots, n, \quad (11)$$
$$W_i^U + \sum_{j=1, j\neq i}^{n} W_j^L \leq 1, \quad i = 1, \ldots, n, \quad (12)$$
$$\sum_{i=1}^{n} W_j^M = 1, \quad (13)$$

If the fuzzy comparison matrix $\widetilde{A}$ defined by Eq. (6) is a precise comparison matrix about the fuzzy weight vector $\widetilde{W}$, namely,

$$\widetilde{a} = (l_{ij}, m_{ij}, u_{ij}) \approx \frac{(w_i^l, w_i^m, w_i^u)}{(w_j^l, w_j^m, w_j^u)}$$

for all $i, j = 1, \ldots, n$; but $j \neq i$, then $\widetilde{A}$ must be able to be written as

$$\begin{bmatrix} 1 & \frac{(w_1^l, w_1^m, w_1^u)}{(w_2^l, w_2^m, w_2^u)} & \cdots & \frac{(w_1^l, w_1^m, w_1^u)}{(w_n^l, w_n^m, w_n^u)} \\ \frac{(w_2^l, w_2^m, w_2^u)}{(w_1^l, w_1^m, w_1^u)} & 1 & \cdots & \frac{(w_2^l, w_2^m, w_2^u)}{(w_n^l, w_n^m, w_n^u)} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{(w_n^l, w_n^m, w_n^u)}{(w_1^l, w_1^m, w_1^u)} & \frac{(w_1^l, w_1^m, w_1^u)}{(w_2^l, w_2^m, w_2^u)} & \cdots & 1 \end{bmatrix} \quad (14)$$

According to the division operation rule of fuzzy arithmetic, i.e. $\frac{(b^L, b^M, b^U)}{(d^L, d^M, d^U)} = (b^L/d^U, b^M/d^M, b^U/d^L)$, where (b^L, b^M, b^U) and (d^L, d^M, d^U) are two positive triangular fuzzy numbers, the fuzzy comparison matrix $\widetilde{A}$ defined by Eq. (14) can be further expressed as

$$\begin{bmatrix} 1 & \left(\frac{w_1^l}{w_2^l},\frac{w_1^m}{w_2^m},\frac{w_1^u}{w_2^u}\right) & \cdots & \left(\frac{w_1^l}{w_n^l},\frac{w_1^m}{w_n^m},\frac{w_1^u}{w_n^u}\right) \\ \left(\frac{w_2^l}{w_1^l},\frac{w_2^m}{w_1^m},\frac{w_2^u}{w_1^u}\right) & 1 & \cdots & \left(\frac{w_2^l}{w_n^l},\frac{w_2^m}{w_n^m},\frac{w_2^u}{w_n^u}\right) \\ \vdots & \vdots & \cdots & \vdots \\ \left(\frac{w_n^l}{w_1^l},\frac{w_n^m}{w_1^m},\frac{w_n^u}{w_1^u}\right) & \left(\frac{w_n^l}{w_2^l},\frac{w_n^m}{w_2^m},\frac{w_n^u}{w_2^u}\right) & \cdots & 1 \end{bmatrix} \quad (15)$$

which can be split into three crisp nonnegative matrices, as shown below:

$$A_L = \begin{bmatrix} 1 & \frac{w_1^l}{w_2^l} & \cdots & \frac{w_1^l}{w_n^l} \\ \frac{w_2^l}{w_1^l} & 1 & \cdots & \frac{w_2^l}{w_n^l} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{w_n^l}{w_1^l} & \frac{w_n^l}{w_2^l} & \cdots & 1 \end{bmatrix}$$

$$A_M = \begin{bmatrix} 1 & \frac{w_1^m}{w_2^m} & \cdots & \frac{w_1^m}{w_n^m} \\ \frac{w_2^m}{w_1^m} & 1 & \cdots & \frac{w_2^m}{w_n^m} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{w_n^m}{w_1^m} & \frac{w_n^m}{w_2^m} & \cdots & 1 \end{bmatrix} \quad A_U = \begin{bmatrix} 1 & \frac{w_1^u}{w_2^l} & \cdots & \frac{w_1^u}{w_n^l} \\ \frac{w_2^u}{w_1^u} & 1 & \cdots & \frac{w_2^u}{w_n^u} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{w_n^u}{w_1^u} & \frac{w_n^u}{w_2^u} & \cdots & 1 \end{bmatrix}$$

It is easy to verify that

$$A_L W_U = W_U + (n-1)W_L, \quad (16)$$
$$A_U W_L = W_L + (n-1)W_U, \quad (17)$$
$$A_M W_M = nW_M, \quad (18)$$

Eqs. (16) – (18) cannot always hold. In the case that they do not hold, we introduce the following deviation vectors:

$$E = (A_L - I)W_U - (n-1)W_L, \quad (19)$$
$$\Gamma = (A_U - I)W_L - (n-1)W_U, \quad (20)$$
$$\Delta = (A_M - nI)W_M, \quad (21)$$

where $E = (\varepsilon_1, \dots, \varepsilon_n)^T$, $\Gamma = (\gamma_1, \dots, \gamma_n)^T$, $\Delta = (\delta_1, \dots, \delta_n)^T$, I is an $n \times n$ unit matrix, ε_i, γ_i and δ_i for $i = 1, \dots, n$ are all deviation variables. It is most desirable that the absolute values of the deviation variables be kept as small as possible, which enables us to construct the following nonlinear goal programming (NGP) model for determining the fuzzy weight vector $\widetilde{W}$:

Minimize $J = \sum_{i=1}^{n}(\varepsilon_i^{+} + \varepsilon_i^{-} + \gamma_i^{+} + \gamma_i^{-} + \delta_i) = e^T(E^{+} + E^{-} + \Gamma^{+} + \Gamma^{-} + \Delta)$

$$(A_L - I)W_U - (n-1)W_L - E^{+} + E^{-} = 0,$$
$$(A_U - I)W_L - (n-1)W_U - \Gamma^{+} + \Gamma^{-} = 0,$$
$$(A_M - nI)W_M - \Delta = 0,$$
$$W_i^L + \sum_{j=1, j\neq i}^{n} W_j^U \geq 1, \quad i = 1, \dots, n,$$
$$W_i^U + \sum_{j=1, j\neq i}^{n} W_j^L \geq 1, \quad i = 1, \dots, n,$$
$$\sum_{i=1}^{n} W_j^M = 1,$$
$$W_U - W_M \geq 0,$$
$$W_M - W_L \geq 0,$$
$$W_L, E^{+}, E^{-}, \Gamma^{+}, \Gamma^{-}, \Delta \geq 0, \quad (22)$$

3.2. The Fuzzy TOPSIS method

This study uses this method to obtain the value of priority and to rank alternatives. TOPSIS views a MADM problem with m alternatives as a geometric system with m points in the n-dimensional space. The method is based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. TOPSIS defines an index called similarity to the positive-ideal solution and the remoteness from the negative-ideal solution. Then the method chooses an alternative with the maximum similarity to the positive-ideal solution (Wang, 2007). It is often difficult for a decision-maker to assign a precise performance rating to an alternative for the attributes under consideration. The merit of using a fuzzy approach is to assign the relative importance of attributes using fuzzy numbers instead of precise numbers. This section extends the TOPSIS to the fuzzy environment (Yang et al, 2007). This method is particularly suitable for solving the group decision-making problem under fuzzy environment. We briefly review the rationale of fuzzy theory before the development of fuzzy TOPSIS. The mathematics concept borrowed from (Ashtiani et al, 2008 & Buyukozkan et al, 2007).

Step 1: Determine the weighting of evaluation criteria
A systematic approach to extend the TOPSIS is proposed to ranking strategies under a fuzzy environment in this section. In this paper the importance weights of various criteria and the ratings of qualitative criteria are considered as linguistic variables (as Table 1) (Chen et al, 2006).

Table 1. Linguistic scales for the importance of each criterion

Linguistic variable	Corresponding triangular fuzzy number
Very low (VL)	(0.0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very high (VH)	(0.7, 0.9, 1.0)

Step 2: Construct the fuzzy decision matrix and choose the appropriate linguistic variables for the alternatives with respect to criteria

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_M \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_N \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array}$$

$i=1,2,\ldots,m$; $j=1,2,\ldots,n$

$$\tilde{x}_{ij} = \frac{1}{k}(\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + \ldots + \tilde{x}_{ij}^k) \quad (28)$$

where $\tilde{x}_{ij}^k$ is the rating of alternative A_i with respect to criterion C_j evaluated by K expert and $\tilde{x}_{ij}^k = (a_{ij}^k, b_{ij}^k, c_{ij}^k)$

Step 3: Normalize the fuzzy decision matrix

The normalized fuzzy decision matrix denoted by $\tilde{R}$ is shown as following formula:

$$\tilde{R} = [\tilde{r}_{ij}]_{m\times n}, \quad i= 1,2,\ldots,m; j=1,2,\ldots,n \quad (29)$$

Then the normalization process can be performed by following formula:

Where $\tilde{r}_{ij} = (\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+})$ $c_j^+ = \max_i c_{ij}$

The normalized $\tilde{r}_{ij}$ are still triangular fuzzy numbers. For trapezoidal fuzzy numbers, the normalization process can be conducted in the same way. The weighted fuzzy normalized decision matrix is shown as following matrix $\tilde{V}$:

$$\tilde{v} = [\tilde{v}_{ij}]_{m\times n}, \quad i= 1,2,\ldots,m; j=1,2,\ldots,n \quad (30)$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \quad (31)$$

Step 4: Determine the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS)

According to the weighted normalized fuzzy decision matrix, we know that the elements $\tilde{V}_{ij}$ are normalized positive TFNs and their ranges belong to the closed interval [0, 1]. Then, we can define the FPIS A^+ and FNIS A^- as following formula:

$$A^+ = (\tilde{V}_1^+, \tilde{V}_2^+, \ldots, \tilde{V}_n^+) \quad (32)$$

$$A^- = (\tilde{V}_1^-, \tilde{V}_2^-, \ldots, \tilde{V}_n^-) \quad (33)$$

where $\tilde{V}_j^+ = (1,1,1)$ and $\tilde{V}_j^- = (0,0,0)$ $j=1, 2,\ldots, n$

Step 5: Calculate the distance of each alternative from FPIS and FNIS.

The distances (d_i^+ and d_i^-) of each alternative A^+ from and A^- can be currently calculated.

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{V}_j^+), \quad i=1,2,\ldots,m \quad j=1,2,\ldots,n \quad (34)$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{V}_j^-), \quad i=1,2,\ldots,m \quad j=1,2,\ldots,n \quad (35)$$

Step 6: Obtain the closeness coefficient (CC_i) and rank the order of alternatives

The CC_i is defined to determine the ranking order of all alternatives once the d_i^+ and d_i^- of each alternative have been calculated. Calculate similarities to ideal solution. This step solves the similarities to an ideal solution by formula:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad i=1,2,\ldots,m \quad (36)$$

According to the CC_i, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives.

4. A Numerical Application of Proposed Approach

This paper, the proposed methodology that may be applied to a wide range of technology selection problems is used for robot selection. We considered cost as a non-beneficial attribute and Vendor reputation, Load capacity and Velocity and as beneficial attributes for Technology selection. These attributes are taken from Farzipoorsaen (2006). These attributes are shown in Table 2.

Table 2. Attributes for robot selection

criteria	Attributes
C_1	Cost (10000$)
C_2	Vendor reputation
C_3	Load capacity(kg)
C_4	Velocity(m/s)

In this paper, the weights of criteria are calculated using of LGP, and these calculated weight values are used as Fuzzy TOPSIS inputs. Then, after Fuzzy TOPSIS calculations, evaluation of the alternatives and selection of technology is realized.

Linear Goal Programming:

In LGP, firstly, we should determine the weights of each criterion by utilizing pair-wise comparison matrices. We compare each criterion with respect to other criteria. You can see the pair-wise comparison matrix for Flexible Manufacturing System criteria in Table 3.

Table 3. Inter-criteria comparison matrix

P	C_1			C_2			C_3			C_4		
	L	m	u	L	m	u	L	m	u	L	m	u
C_1	1.00	1.00	1.00	4.00	5.07	6.50	2.00	2.90	3.97	0.25	1.84	3.66
C_2	0.15	0.20	0.26	1.00	1.00	1.00	1.85	3.08	4.00	0.87	1.33	1.97
C_3	0.26	0.39	0.61	0.25	0.32	0.54	1.00	1.00	1.00	1.17	2.23	2.96
C_4	0.28	0.55	4.59	0.58	0.84	1.18	0.46	0.70	3.32	1.00	1.00	1.00

After forming the model (22) for the comparison matrix and solving this model, the weight of criteria are obtained and are shown as follow:

w^t= (0.4170, 0.2223, 0.1253, 0.2353) ^{T}

Fuzzy TOPSIS:

The weights of the criteria are calculated by LGP up to now, and then these values can be used in Fuzzy TOPSIS. So, the Fuzzy TOPSIS methodology must be started at the second step. Thus, weighted normalized decision matrix can be prepared. This matrix can be seen from Table 4.

Table 4. The weighted normalized decision matrix

	C_1			C_2			C_3			C_4		
A_1	0.07	0.09	0.09	0.07	0.10	0.10	0.06	0.08	0.08	0.05	0.08	0.11
A_2	0.02	0.05	0.07	0.00	0.00	0.02	0.02	0.04	0.06	0.03	0.05	0.08
A_3	0.00	0.02	0.05	0.02	0.05	0.07	0.04	0.06	0.08	0.00	0.03	0.05
A_4	0.02	0.05	0.07	0.05	0.07	0.10	0.04	0.06	0.08	0.00	0.03	0.05

By following Fuzzy TOPSIS procedure steps and calculations, the ranking of alternatives are gained. The results and final ranking are shown in Table 5.

Table 5. The result of Fuzzy TOPSIS method

	d_i^+	d_i^-	CC_i	Rank
A_1	1.32	1.20	0.47	4
A_2	0.81	1.56	0.65	2
A_3	1.22	1.39	0.53	3
A_4	0.41	1.74	0.80	1

According to Table 5, A_4 is the best alternative among other.

5. Conclusions

Selecting the right technology is always a difficult task for decision-makers. Technologies have varied strengths and weaknesses which require careful assessment by the purchasers. This paper illustrates an application of Linear Goal Programming along with Fuzzy TOPSIS in selecting best technology. Fuzzy set theory is incorporated to overcome the vagueness in the preferences. A two-step LGP and Fuzzy TOSIS methodology is structured here that Fuzzy TOPSIS uses LGP result weights as input weights. Then a numerical example is presented to show applicability and performance of the methodology.

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Acknowledgement
The authors wish to thank an anonymous referee for the valuable suggestions which considerably improve the quality of the paper.

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5/11/2013