# Making E-Business Customer Focused: A Fuzzy Approach

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## ABSTRACT

*In this paper a methodology has been introduced to make the e-business more customers focused by obtaining the preference ranking of the products as per the buyers' choice. The methodology takes into account the multiplicity of the product attributes and works in an integrated approach of fuzzy logic and Ordered Weighted Average Operator (OWA). The concept of OWA is used here to measure the optimism level of the customers in the given e-business system. This is most valuable information to make the e-business customer focused. Further, the OWA is applied here to articulate the targeted customers thereby making the e-business more customers' orientation.*

## 1. INTRODUCTION

In any business whether it is online or traditional, a customer evaluates all available products as a whole before ranking them according to his or her own preferences. The ranking is specific to a particular customer and it normally depends on the number of products available to the customer in the market and how the product features satisfy to his/her likings. A customer's preferences for the products and hence their rankings are implicit in his/her mind and are difficult to express explicitly.

No doubt that each customer likes to have the fullest satisfaction on all the desired attributes of the products. However, the product attributes are in general conflicting, non-commensurable and fuzzy in nature and it is very difficult to satisfy all of them simultaneously. In this situation, a customer makes effort to satisfy most of the attributes rather than all of them. By the process, the customer is attaching some weights to the product attributes. These underlying weights are implicit in customers' mind. Articulation of these hidden weights will not only make the business more customers focused but also will help the business in analyzing the need of the customers in terms of the product requirements. The enunciation of these weights is a very complex and difficult task. In traditional markets, a sales person can assess these weights to some extent while interacting with the customers and through their body language. However, in e-business where no direct interaction takes place amongst the business partners, the identification of these weights is next to impossible. This problem becomes further complicated when the customers' requirements regarding the product specifications are imprecise or fuzzy in nature. In our paper we have introduced a methodology based on fuzzy sets to handle this problem in the e-business system.

In the literature, several papers refer to e-business sites. Jango and "Deal Time" (www.dealtime.com) are the earlier e-business market places. These sites collect information regarding the customers about their product preferences along with their prices and futures from the internet, and based on the information collected, suggest suitable products to the customers. However, it is difficult for the buyers to decide about an appropriate product in the vast Internet market. The agents such as "decision guide" by www.ActiveBuyersGuide.com assist the customers in identifying a suitable product. This e-business site requires the data from the buyers: the importance of the attributes numerically or in a range. The "decision guide" hardly accepts customer's fuzzily defined product specifications. These characteristics of www.ActiveBuyers.com fail to attract the customers.

A product classification problem in e-market is given in [5] and the classification of the products was based on their attributes. This procedure searches for a suitable product in the Internet, based on the customers' attribute wise requirements and if a product is found, the search ends. In case of non-availability, the procedure chooses a next available product closest to the targeted product. The drawback in the work [5] is the term attribute flexibility which was defined subjectively. The concept of attribute flexibility helps in classifying different products having different attribute values into the same preference group. The procedure given in [4] extends the idea of [5]. In [5], the subjective assumptions of the attribute flexibility are replaced by their objective counter parts. In [5], the available products in the e-business site are hierarchically classified based on their attribute values in a sequential manner. For example, in a CAR purchasing problem the possible attributes may be cost, maintenance-cost, and mileage. First the Cars are selected with respect to cost, then with respect to maintenance-cost, from the selected ones through cost attribute and finally by mileage from the Cars passed through the test of maintenance-cost. However, the deficiency of this approach is that the order in which the attributes are used to screen the products is arbitrary and does not reflect customers' anticipated priority about the attributes while making the final choice.

The present work addresses this problem by calculating the overall assessment of the products by using linguistic quantifiers [3] and OWA (Ordered Weighted Average) operators [6]. The procedure presented in this paper also helps to find the level of optimism of the customers and also the targeted customers. These are important aspect of e-business to make it more customers' focused. Optimism level of customers gives e-business companies become aware of the extent to which it is customer focused. On the other hand, the targeted customer determination helps the e-business system to focus on the valuable customers.

## 2. FUZZY CONCEPTS IN PRODUCT ATTRIBUTES

In any product purchase, normally a customer expresses his/her desire in multiple product attributes, which in general are fuzzy. For example in a car purchasing problem, the attributes may be price, re-sale value, mileage, maintenance etc. Very often a customer views these attributes fuzzily as shown in the italic words below:

Price should be *around US$ 2000*
The re-sale value should be *OK*
Mileage should be *normal*
Maintenance cost should not be *very high*.

We can define the above fuzzily defined terms as fuzzy numbers [1, 2, 4]. For example, the terms "*around US$ 20000*" and "*normal*" can be represented as fuzzy numbers as shown in figures 1 and 2 below.

*Figure 1*

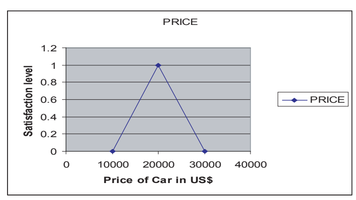
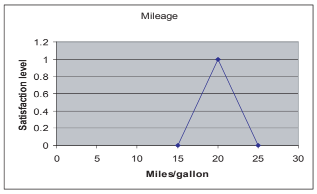


*Figure 2*




## 3. OWA OPERATORS IN E-BUSINESS

We have used OWA here to measure how far an e-business system is customer focused under a given product profile and what strategies are needed to improve the same. This is done by determining the preference ranking of the products as per the buyers' choice, optimism level of the buyers and through the identification of the targeted customers.

### 3.1 OWA Operator

An OWA operator of dimension n is a mapping f: $R^n \rightarrow R$ that has an associated *n* vector $(w_1, w_2, ..., w_n)^T$ such that $w_i$ ε [0,1] and $\sum w_i = 1$.

If $a_1, a_2 .., a_n$ are the elements to be aggregated (here they refer to product attribute levels) their aggregated value through OWA operator is:

$$f(a_1, a_2, ..., a_n) = \sum_j w_j b_j \quad \ldots \quad (3.1)$$

Where $b_j$ is the jth largest amongst $a_j$.

The OWA operator uses the linguistic quantifier from the customers to derive the weights for the OWA operator. We consider the linguistic quantifier "most" following the [3] as follows.

$$\mu_{most}(x) = \begin{cases} 1 & x \geq 0.8 \\ \dfrac{(x-0.3)}{0.5} & 0.3 \leq x \leq 0.8 \\ 0 & x \leq 0.3 \end{cases} \quad \ldots. \quad (3.2)$$

The weights for the OWA can be obtained through the following equation [6].

$$w_i = Q(i/n) - Q((i-1)/n) \qquad \text{for } i = 1, 2, \ldots n \qquad (3.3)$$

### 3.2 Product Ranking

Let us assume that K products ($P_1, P_2 \ldots P_K$) are available on the Internet. Let each product Pi ($i$ =1, 2 …, K) has *m* attributes ($A_{ij}$) ($i$ = 1, 2… K and $j$ = 1, 2… m). $A_{ij}$ represents the $j^{th}$ attribute of the $i^{th}$ product. Let $s_1, s_2 \ldots, s_m$ represent the customer's attribute-wise requirements in the form of fuzzy sets as:

$\{(s_1, \mu_{s1})\}, \{(s_2, \mu_{s2})\} \ldots, \{(s_m, \mu_{sm})\}$

Where $\mu_{sj}$ ($j$ =1, 2, 3 …, m) represents the membership value of the customer's specifications on the attribute *j*.

Initially the e-business system presents the available products to the customers. After evaluating the products, generally customers form an overall opinion about the products fuzzily through linguistic quantifiers such as; mostly, more or less etc. The product rating of the product $P_i$ can be derived through the OWA operator as given below.

$$F_Q(\mu_1(A_{i1}), \mu_2(A_{i2}) \ldots, \mu_n(A_{in})) = \sum_i w_i b_j = R(P_i) \; i = 1,2, \ldots K \quad \ldots(3.4)$$

where $b_j$ is the $j_{th}$ largest of the $\mu_{si}(A_{ij})$. The weights in the above equation are determined using equation (3.3).The value $R$ ($P_i$) is the rating of the product $P_i$.

Since these values are numerical numbers, they can be ranked from the best preferred product to the least preferred one. Note that the products are ranked here as per the buyer's choice.

### 3.3 Optimism Level of the Customers

The concepts of OWA operator and the weights therein provide a measure of orness [6] (optimism) and it is defined by the equation (3.5) below.

$$\text{Or-ness}\,(W) = \frac{1}{m-1}\sum_{i=1}^{m}(m-i)w_i \qquad (3.5)$$

The or-ness measure helps the e-business companies become aware of the extent to which it is customer focused in a given product profile. If the customers are absolutely optimistic we have

$$F_Q{}^*(\mu_{s1}(A_{i1}), \mu_{s2}(A_{i2}), \ldots \mu_{sn}(A_{in})) = Max(\mu_{s1}(A_{i1}), \mu_{s2}(A_{i2}), \ldots, \mu_{sn}(A_{in})) \qquad (3.6)$$

The weights are here (0, 0, 0 …1).

Similarly if the customers are pessimistic about the products we have

$$F_{Q*}(\mu_{s1}(A_{i1}), \mu_{s2}(A_{i2}), \ldots, \mu_{sn}(A_{in})) = Min[\mu_{s1}(A_{i1}), \mu_{s2}(A_{i2}), \ldots, \mu_{sn}(A_{in})] \qquad (3.7)$$

The weights are as (1, 0, 0 ….0).

### 3.3 The Targeted Customer Identification

It is very important for a business to identify its most valuable customers in totality. In the context of e-business, however, it is difficult to identify them. In the event of high demand and low stock level, it is an important issue. The purpose of this paper is to find strategies for the selection of these targeted customers under limited products. The procedure first evaluates different customers' ratings of the desired products. Then the customer corresponding to the maximum rating is selected as the targeted customer. The next higher rating determines the second-best targeted customer and so on. This methodology is explained in the following steps.

**Step.1** If there are p numbers of customers, $C_2 \ldots, C_p$ and they require the products as follows (P=3, say) we have:

$C_1$: $P_i, P_j, P_k$

$C_2$: $3P_i, P_j, P_r$

$C_3$: $2P_i, P_r, P_u, P_t$

(The coefficient 3 for $C_2$ indicates the number of the product $P_i$ as required by $C_2$)

**Step.2** Take their attribute-wise satisfaction levels.

For $C_1$:

$$\begin{array}{ll} P_i & [(A_{i1}, \mu_{s1}(A_{i1})), (A_{i2}, \mu_{s2}(A_{i2})), \ldots, (A_{im}, \mu_{sm}(A_{im}))] \\ P_j & [(A_{j1}, \mu_{s1}(A_{j1})), (A_{j2}, \mu_{s2}(A_{j2})), \ldots, (A_{jm}, \mu_{sm}(A_{jm}))] \\ P_k & [(A_{k1}, \mu_{s1}(A_{k1})), (A_{k2}, \mu_{s2}(A_{k2})), \ldots, (A_{km}, \mu_{sm}(A_{km}))] \end{array} \qquad (3.8)$$

For $C_2$:

$$\begin{array}{ll} 3P_i & [(A_{i1}, \mu_{s1}(A_{i1})), (A_{i2}, \mu_{s2}(A_{i2})), \ldots, (A_{im}, \mu_{sm}(A_{im}))] \\ P_j & [(A_{j1}, \mu_{s1}(A_{j1})), (A_{j2}, \mu_{s2}(A_{j2})), \ldots, (A_{jm}, \mu_{sm}(A_{jm}))] \\ P_r & [(A_{r1}, \mu_{s1}(A_{r1})), (A_{r2}, \mu_{s2}(A_{r2})), \ldots, (A_{rm}, \mu_{sm}(A_{rm}))] \end{array} \qquad (3.9)$$

For $C_3$:

| | |
|---|---|
| $2P_j$ | $[(A_{j1}, \mu_{s1}(A_{j1})), (A_{j2}, \mu_{s2}(A_{j2})), \ldots, (A_{jm}, \mu_{sm}(A_{jm}))]$ |
| $P_r$ | $[(A_{r1}, \mu_{s1}(A_{r1})), (A_{r2}, \mu_{s2}(A_{r2})), \ldots, (A_{rm}, \mu_{sm}(A_{rm}))]$ |
| $P_u$ | $[(A_{u1}, \mu_{s1}(A_{u1})), (A_{u2}, \mu_{s2}(A_{u2})), \ldots, (A_{um}, \mu_{sm}(A_{um}))]$ |
| $P_t$ | $[(A_{t1}, \mu_{s1}(A_{t1})), (A_{t2}, \mu_{s2}(A_{t2})), \ldots, (A_{tm}, \mu_{sm}(A_{tm}))]$ (3.10) |

**Step 3.** For each customer add the attribute totals of every attribute. For customer $C_1$ we have the total attributes for the ith, jth and the kth products are as follows:

$$C_1(A_z) = \frac{1}{3}(\mu_s(A_{iz}) + \mu_s(A_{jz}) + \mu_s(A_{kz})) \quad z = 1, 2\ldots m \qquad (3.11)$$

The index $z$ represents the $z^{th}$ attribute. Similarly we can have $C_2(A_z)$ and $C_3(A_z)$ for the $2^{nd}$ and $3^{rd}$ customer.

**Step.4** Use the aggregated weights from equation (3.4) and apply the OWA operator to $C_1(A_z)$ (z =1, 2… m); the product rating of customer $C_1$ is

$$R(C_1) = \sum_{z=1}^{m} w_z q_z \qquad (3.12)$$

Where $q_z$ is the $j_{th}$ largest among $C_1(A_z)$. Similarly, product ratings of second and third customers can be obtained as $R(C_2)$ and $R(C_3)$ respectively. Since these product ratings of the individual customers are numerical quantities, they can be ordered. In this approach the customer with the highest rating is considered to be the best customer in the customers' hierarchy. The next best customer in the hierarchy is accorded the second highest rating and so on.

## 4. NUMERICAL EXAMPLE

Let us assume that the customer's requirements for a product (e.g., a car) are expressed in terms of attributes cost, maintenance-cost (monthly) and mileage (miles/gallon). The attributes are in the form of fuzzy sets as shown below.

Cost = {0/10,000, 0.8/15,000, 1.0/20,000, 0.8/25,000, 0.6/30,000, 0.4/40,000, 0.1/50,000, 0/60,000}
Maintenance = {0/40, 0.4/50, 0.63/100, 0.65/150, 1.0/200,0.8/300, 0.4/400, 0.2/500}
Mileage = {0/9, 0.1/10, 0.4/12, 0.5/15, 0.6/16, 0.73/17, 0.8/19, 1.0/20, 0.9/21, 0.8/22, 0.72/25, 0.7/26}

Let us assume that there are eight types of cars available on the Internet. The data regarding these cars are given in Table 1.

**Product Ranking**
Using equations (3.2) and (3.3) the aggregated weights to the attributes are:

$w_1 = Q(1/3) - Q(0/3) = Q(0.33) - Q(0) = \mu_{most}(0.33) - 0 = 0.06$. Similarly, $w_2 = 0.66$ and $w_3 = 0.28$.

Now by using equation (3.4) we can get the product ratings are: $R(P_1) = FQ(0.6, 0.63, 0.8) = 0.632$.

Similarly, $R(P_2) = 0.419$, $R(P_3) = 0.792$, $R(P_4) = 0.492$, $R(P_5) = 0.5$, $R(P_6) = 0.7$, $R(P_7) = 0.368$ and $R(P_8) = 0.812$. From the above it can be determined that the customers' preference ranking of the products can be ordered as:

$P_8$, $P_3$, $P_6$, $P_1$, $P_5$, $P_4$, $P_2$ and $P_7$.

**Level of Optimism**
From equation (3.5) with aggregated weights as $w_1 = 0.06$, $w_2 = 0.66$ and $w_3 = 0.28$; $m = 3$, the or-ness or degree of optimism of the customers is:

1/2([(3-1)0.06 + (3-2)0.66+ (3-3)0.28] = 0.39

This demonstrates that the customers' level of optimism at the present system is approximately 40%.

**Targeted Customers**
Assume there are three customers who would like to purchase the products as given below

$C_1$: $P_1$, $2P_2$, $P_3$

$C_2$: $P_1$, $P_3$, $P_5$

$C_3$: $2P_1$, $P_3$, $P_2$

Let the company has one product each of type $P_1$, $P_2$, $P_3$, $P_4$, $P_5$, $P_6$, $P_7$, $P_8$. Now the question is how to choose the customers. First consider customer $C_1$. Using equation (3.11) the attribute totals of customer $C_1$ are

$C_1(A_1) = 1/3[0.6+0.4+1] = 0.67$

Note that for $P_2$ the second attribute's satisfaction has been added once, because the company does not have two $P_2$s.

$C_1(A_2) = 1/3[0.63+0.4+0.8] = 0.61$

*Table 1. Sample data for products*

| Car type | Cost in US$ | $\mu_{cost}$ | Maintenance Cost in US$ | $\mu_{maintenance}$ | Mileage in (miles/gal) | $\mu_{mileage}$ |
|---|---|---|---|---|---|---|
| $P_1$ | 30,000 | 0.6 | 100 | 0.63 | 19 | 0.8 |
| $P_2$ | 40,000 | 0.4 | 50 | 0.4 | 25 | 0.72 |
| $P_3$ | 20,000 | 1.0 | 300 | 0.8 | 17 | 0.73 |
| $P_4$ | 50,000 | 0.1 | 100 | 0.63 | 22 | 0.8 |
| $P_5$ | 50,000 | 0.1 | 150 | 0.65 | 25 | 0.72 |
| $P_6$ | 40,000 | 0.4 | 200 | 1 | 22 | 0.8 |
| $P_7$ | 15,000 | 0.8 | 500 | 0.2 | 12 | 0.4 |
| $P_8$ | 25,000 | 0.8 | 300 | 0.8 | 20 | 1.0 |

$C_1(A_3) = 1/3[0.8+0.72+0.73] = 0.75$

Based on the product requirements and the availability, we can obtain the customer's aggregated rating for the products can be obtained following the equation (3.17) as: $R(C_1) = 0.06(0.75)+0.66(0.67)+0.28(0.61) =0.658$. Similarly we have $R(C_2) = 0.66$ and $R(C_3) = 0.658$. This indicates that an e-business system should target the $C_2$ first and then $C_1$ and $C_3$ equally.

## 5. CONCLUSION

In this research, customers' imprecise judgments are treated in terms of fuzzy logic and their compromising attitudes are handled by linguistic quantifiers Then, OWA operators are used as excellent tools for producing an overall ranking of products in a fuzzy e-business environment. Such applications of these recently developed techniques are lacking in the literature. It has been demonstrated that this approach makes it possible to calculate levels of customer optimism or pessimism. Businesses on the Internet are expected to benefit from such a measure as it will help them become more customer-focused and gain competitive advantage.

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