Multi Agent E-Marketplace Based on Weighted OCEAN Personality Model

Aboozar Hemmati[1*] and Aboozar Barzegar[2]

***Abstract*—**The advent of mobile and intelligent agent technology has entered the E-commerce into a new era of its life. In this paper, we present a model based on weighted OCEAN model of personality for buyer and seller agents in multi agent-based electronic marketplaces. Four important factors: personality, reputation, quality, and price are considered in the model. We take into account the fact that buying agents with different personality can have different priorities on reputation, quality, and price of their goods and selling agents adjust their bids according to buying agents preferences. Also we have assumed that multiple selling agents with different personality may offer the same goods with different qualities and prices. The personality of buyer and seller agents influences their behavior in market. Buyer agents use their own personality to assess the value of seller agents' bids. Also buyer agents apply reinforcement learning to evaluate the reputation of seller agents based on their personality and then focus their trading on the most reputable sellers. On the other hand, seller agents adjust their bids according to buyer agents' preferences and their own personality. In addition, seller agents apply reinforcement learning to model the reputation of buyer agents. We have implemented this model with Aglet. The results show that selling/buying agents that model the reputation of buying/selling agents based on their personality achieve more satisfaction in comparison with the selling/buying agents who only use the reinforcement learning.

***Keywords*—**E-Commerce, E-Marketplace, Agent, OCEAN personality model, Reinforcement learning, Reputation.

I. Introduction

E-MARKETPLACES play a big role in e-commerce. The e-marketplace is a virtual marketplace where buyers and suppliers meet to exchange information about product and service offers, and to negotiate and carry out business transactions [3]. Furthermore, in the age of the Internet and with the emergence of new information and communication technologies, the e-marketplace is a Web-based information system, where multiple suppliers and multiple buyers can undertake business transactions via the Internet [4].

Bringing together large numbers of sellers and buyers on the e-marketplace enables sellers to enter new markets, to find new buyers, and to increase sales. On the other hand, the e-marketplace gives a buyer access to a wide range of goods offered by sellers. Buyers have the opportunity to quickly evaluate various offers by price, quality and performance measures. E-marketplaces give sellers access to new buyers, expand the options available to buyers, and reduce transaction costs. The e-marketplace services support the exchange of large amounts of data about the supply and demand between the buyer and seller, and the implementation of business [1].

With the advent of mobile and intelligent agent technology, e-commerce has entered into a new era of its life [2]. Mobile agents are intelligent, independent, and proactive electronic representatives of businesses such as sellers and buyers agent. They add even more business opportunities because they can represent a company on different marketplaces in the world at the same time without human involvement. One of the most important consequences of applying agent technology over E-commerce is agent-based E-Marketplace. In the recent years, the extensive investigations are concentrated on designing agent-based E-Marketplaces. The lack of Intelligence in trading agents is one of the most important problems which can be mentioned in these studies.

Roozmand et al [5] propose a market model which is based on reputation and reinforcement learning algorithms for buying and selling agents. Three factors are considered in this market: quality, price and delivery. In this model each selling agent models the reputation of buyers and dedicates them discount based on their reputation.

In recent years there has been an increased interest in dispersed approaches to modeling complex real-world problems. Buyer and seller behavior research involves different areas: sociology, economics, psychology, marketing and engineering. Personality is one of the most important factors which profoundly affect the behavior of both buyers and sellers. Behaviors are influenced by personalities, so that personality refers to sets of predictive behaviors by which people are recognized and identified [8].

There are some researches which prove that personality is strongly connected to consumer purchase decision making process. Different consumers have different characteristics in their life that also influences their buying behavior. Social factors (such as family, groups, roles and status) and personal

[1] Islamic Azad University, Lamerd Branch, Department of Science, Lamerd, Iran

[2] Islamic Azad University, Lamerd Branch, Department of Engineering, Lamerd, Iran.

factors (such as age, occupation, lifestyle, personality and self-concept) are those characteristics that could manipulate the buyer behavior in making final decision [10]. Personality is consistent and enduring. Although marketers can't change consumer personalities to conform to their products, if they know which personality characteristics influence specific consumer responses, they can attempt to appeal to the relevant traits inherent in their target group of customers [9]. The researches show that differences in personality types cause differences in trading behaviors of people. Therefore, applying personality traits to e-commerce agents can make them more realistic and humanlike.

T. Zhang and D. Zhang [6] present a model for consumer purchasing decision making process based on lifestyle and personality traits. The core of this model is a motivation function that combines consumers' psychological personality traits with two important kinds of interactions in a competitive market. The model reveals the inner psychological mechanism on the basis of which consumers make their choices when facing competing brands on the market.

Barzegar et al [7] propose a market model based on personality and reinforcement learning for buyer and seller agents. As they mention, it is so complex to consider all personality traits for buyer and seller agents. So just two personality traits are used in this market. Openness and stingy for buyers and stingy and conscientiousness for sellers. Results showed that sellers with low score of stingy earn more benefits and conscientious seller agents gain more reputation. Also, buyer agents with high score of openness and low score of stingy purchase more new goods and more expensive goods.

In order to make agents more human-like and to increase their flexibility, we update above mentioned agent model. The personality is divided in 30 attributes, each one called a personality facet. The personality facets are clustered in five groups, called personality factors or traits. The five-factor model of personality is best known as OCEAN and is the most widely accepted model of personality [11]. This model of personality is a hierarchical organization of personality traits in terms of five basic dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

In this paper, we propose a model based on OCEAN personality model and reinforcement learning for buyer and seller agents in agent-based electronic marketplaces. Four important factors: personality, reputation, quality, and price are considered in the model. What is new in our model is considering all five personality factors of OCEAN model of personality for seller and buyer agents with special weights based on transactions in the market. These weights are determined and updated by market manager for buyers and sellers independently.

II. The Proposed Model

In this section, we propose our model and learning algorithms based on reputation, personality, and reinforcement learning for each buyer and seller agents in four subsections. The key point of this work is considering all personality traits for buyer and seller agents. Each personality trait has special weight according to their relation to transactions in the market.

A. Framework

Framework of an electronic commerce environment includes three types of servers: Marketplace, Selling Agent (SA) and Buying Agent (BA) Server. Each server includes a number of stationary and mobile agents and some consequential transactions between agents in the e-marketplace. There is one static agent (MMA1) and two kinds of mobile agent (MBA2 and MSA3) in the marketplace which is a platform that supports the transaction facilities for mobile agent of buyers and sellers.

B. Definitions

This subsection presents some definitions including notations which are used in the model. For most of the properties, superscript denotes who holds the property while what is in parenthesis denotes who it refers to.

Definition1. For a personality vector $\Psi = (\psi_1, \psi_2, \psi_3, \psi_4, \psi_5)$ and a weight vector $W = (w_1, w_2, w_3, w_4, w_5)$, the personality score based on OCEAN personality model is given by $\Psi_w = \sum_{i=1}^{5} w_i \psi_i$ where $\psi_i \in [0,1]$, $w_i \in [0,1]$ and $\sum_{i=1}^{5} w_i = 1$. ψ_1, ψ_2, ψ_3 , and ψ_4 are the scores of Openness, Conscientiousness, Extroversion, and Agreeableness factors in OCEAN model, respectively. But ψ_5 is the score of emotional stability, the reverse of Neuroticism factor in OCEAN model of personality. In fact Ψ_w is inner product of two vectors W and Ψ that gives a weighted mean of five factors in OCEAN model of personality.

We denote the personality score of a seller s and a buyer b by Ψ_w^s and Ψ_w^b, respectively. Each seller and buyer has a unique personality vector. There are two separated weight vectors for each seller and buyer sets denoted by w^s and w^b respectively. Initial value of these vectors is determined by MMA. These components are refined and updated after each succeeding purchase by MMA.

Definition2. Given a set of goods G, a set of qualities Q, and a set of buyers B, $C^s: G \times Q \times B \to \mathbb{R}$ is the cost function to evaluate the cost of a seller s to produce good g with quality q for buyer b.

Hence, $C^s(g, q, b)$ is a real number representing seller s's calculated cost of producing good g with quality q for buyer b. We denote cost function as C^s for ease of notation.

[1] - Market Manager Agent
[2] - Mobile Buying Agent
[3] - Mobile Selling Agent

Definition3. Given a set of sellers S and a set of buyers B, the personality-based percent of profit function of a seller $s \in S$ is given by $k_{\Psi}^{s}(b) = (1 - \Psi_{w}^{s}) \cdot k$ .In which, $k \in (0,1)$ is the maximum reasonable percent of profit based on market norms. It's clear that $k_{\Psi}^{s}(b)$ is a real number lower than k. Therefore, Sellers with higher score of personality considers lower percent of profit and it means that they discount more. We denote this function as k_{Ψ}^{s} for ease of notation.

Definition4. Given a set of goods G, a set of prices P, and a set of qualities Q, $E^{b}: G \times P \times Q \times S \rightarrow \mathbb{R}$ is the estimator function used by a buyer b to assess the value of a good g given the price, quality and seller. Hence, $E^{b}(g,p,q,s)$ is a real number which represents buyer b's estimated value of buying good g at price p with quality q from seller s. We denote estimator function as E^{b} for ease of notation.

Definition5. Given a set S of sellers and a set B of buyers:

- $r_{q}^{b}: S \rightarrow (-1,1)$ is the reputation function of a buyer $b \in B$ based on quality factor. Buyer b models the reputation of seller $s \in S$ on quality using $r_{q}^{b}(s)$ function. Seller s is reputable for buyer b on quality if $r_{q}^{b}(s) \geq \Theta_{q}^{b}$ where $\Theta_{q}^{b} \in (0,1)$ is buyer b's reputable threshold on quality. And, seller s is disreputable for buyer b on quality if $r_{q}^{b}(s) \leq \theta_{q}^{b}$ where $\theta_{q}^{b} \in (-1,0)$ is buyer b's disreputable threshold on quality.
- $r_{p}^{b}: S \rightarrow (-1,1)$ is the reputation function of a buyer $b \in B$ based on price factor. Buyer b models the reputation of seller $s \in S$ on price using $r_{p}^{b}(s)$ function. Seller s is reputable for buyer b on price if $r_{p}^{b}(s) \geq \Theta_{p}^{b}$ where $\Theta_{p}^{b} \in (0,1)$ is buyer b's reputable threshold on price. And, seller s is disreputable for buyer b on price if $r_{p}^{b}(s) \leq \theta_{p}^{b}$ where $\theta_{p}^{b} \in (-1,0)$ is buyer b's disreputable threshold on price.
- $r^{s}: B \rightarrow (0,1)$ is the reputation function of a seller $s \in S$. Seller s models the reputation of buyer $b \in B$ using $r^{s}(b)$ function. Buyer with high $r^{s}(b)$is considered more reputable.

Definition6. Given a set of sellers S and a set of buyers B, the personality-based general reputation function of a buyer $b \in B$ is given by $r_{\Psi}^{b}(s) = \Psi_{w}^{b} \cdot r_{q}^{b}(s) + (1 - \Psi_{w}^{b}) \cdot r_{p}^{b}(s)$.

Definition7. Given a set S of sellers and a set B of buyers:

- A seller s is considered reputable by buyer b if $r^{b} \geq \Theta_{\Psi}^{b}$, where $\Theta_{\Psi}^{b} \in (0,1)$ is buyer b's personality-based reputation threshold and given by $\Theta_{\Psi}^{b} = \Psi_{w}^{b} \cdot \Theta_{q}^{b} + (1 - \Psi_{w}^{b}) \cdot \Theta_{p}^{b}$.
- A seller s is considered disreputable by buyer b if $r^{b} \leq \theta_{\Psi}^{b}$, where $\theta_{\Psi}^{b} \in (-1,0)$ is buyer b's personality-based disreputation threshold and given by $\theta_{\Psi}^{b} = \Psi_{w}^{b} \cdot \theta_{q}^{b} + (1 - \Psi_{w}^{b}) \cdot \theta_{p}^{b}$.

A seller s is considered non-reputable by buyer b if $\theta_{\Psi}^{b} < r^{b} < \Theta_{\Psi}^{b}$. In this case, seller s is neither reputable nor disreputable to buyer b. In other words, b does not have enough information to decide on the reputation of s.

C. Transactions

In this subsection, we describe the transactions in the process of trading illustrated in Figure 1:

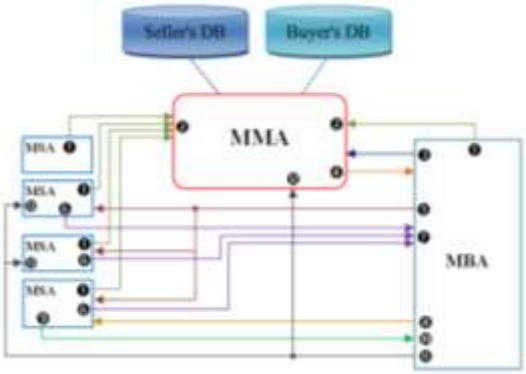

Fig. 1: Model Transactions

1. SA and BA submit registration request and answered personality questionnaire to MMA.
2. MMA calculates SA's and BA's personality scores, then stores them with their registration information in Seller's and Buyer's DBs respectively.
3. BA requests list of sellers who sell specified product from MMA.
4. MMA retrieves relevant sellers and sends list of them to BA.
5. BA multicasts its requests to relevant sellers for specified product.
6. Each SA prepares a bid based on their own personality and BA's reputation and sends it to BA.
7. BA receives all bids, estimates their value based on their own personality and selects the most reputable SA with the best bid.
8. BA announces selected SA and pays it.
9. Selected SA delivers the product to BA and updates the BA's reputation based on their own personality.
10. BA assesses the real value of product and updates the reputation of selected SA based on their own personality.
11. BA multicasts to MMA and relevant unselected SA(s) that the specified product has been bought from selected SA.
12. MMA refines and updates the sellers and buyers' weight vectors.
13. Each relevant unselected SA alters the bid based on their personality to increase the chance to be selected by BA in the next purchase.

D. Algorithms

a. Seller Algorithm

According to definition 1, seller s's personality score is $\Psi_w^s = \sum_{i=1}^{5} w_i^s \psi_i^s$. In which $\Psi^s = (\psi_1^s, \psi_2^s, \psi_3^s, \psi_4^s, \psi_5^s)$ and $W^s = (w_1^s, w_2^s, w_3^s, w_4^s, w_5^s)$ are the personality and weight vector of seller s, respectively. Assume that seller s produces good g with quality q for buyer b with the cost of C^s. The maximum price for seller s is calculated by $p_{max}^s = C^s + k \cdot C^s$ but the price that seller s determines based on his personality to sell good g is $p_{bid}^s = C^s + k_\Psi^s \cdot C^s$. It is clear that high score of personality of seller s causes lower price and vice versa. After receiving the buyer request for good g, seller s adjusts the bid for the buyer. This bid includes two factors: quality and price. There are some sellers who try to cheat the buyers by offering high quality goods and delivering them low quality goods. In other word, these sellers do not say the real quality of their goods. Lying about the characteristics of the goods really depends on seller's personality score. In our model seller s adjusts the bid by $q_{bid}^s = q_{real} + (1 - \Psi_w^s) \cdot q_{real}$ in which, q_{real} is the real quality of the good g, and q_{bid}^s is the quality of the good g that seller s offers to buyer b.

If seller s succeeds to sell good g with quality q_{bid}^s at price p to buyer b, it means that seller s has presented a bid better than the other sellers to buyer b. Therefore, seller s may be re-selected by buyer b if seller s repeats this bid again for buyer b for specified good g. Seller s delivers product to buyer b and updates the reputation of buyer b using reinforcement learning as $r^s(b) \leftarrow r^s(b) + \lambda^s \cdot (1 - r^s(b))$. Where, λ^s is a positive factor called personality-based cooperation factor and is equal to $\lambda^s = \Psi_w^s \cdot SRP = \Psi_w^s \cdot \frac{k_\Psi^s}{k}$, in which, SRP [4] is the relative profit for seller s if it could sell good g to b and $SRP = \text{seller profit/maximum profit} = (q_{bid}^s - C^s)/(p_{max}^s - C^s) = k_\Psi^s/k$.

Also, seller s updates its personality-based percent of profit for buyer b by considering reputation of buyer b using reinforcement learning by $k_\Psi^s \leftarrow k_\Psi^s + (1 - r^s(b))(k - k_\Psi^s)$. If seller s does not succeed to sell good g with quality q_{bid}^s at price p to buyer b, seller s reduces the price of the good to sell it in the next purchase to buyer b. It is clear that if seller s does not improve the previous bid, he cannot sell the good. He reduces p_{bid}^s by decreasing k_Ψ^s using $k_\Psi^s \leftarrow (1 - \Psi_w^s) \cdot k_\Psi^s$

b. Buyer Algorithm

According to definition 1, buyer b's personality score is $\Psi_w^b = \sum_{i=1}^{5} w_i^b \psi_i^b$, in which $\Psi^b = (\psi_1^b, \psi_2^b, \psi_3^b, \psi_4^b, \psi_5^b)$ and $W^b = (w_1^b, w_2^b, w_3^b, w_4^b, w_5^b)$ are the personality and weight vectors of buyer b, respectively. The main parts of buyer algorithms are estimator function and reputation modeling. According to definition 3, buyer b estimates the value of all bids offered by each seller using function $E^b = \frac{q_{bid}^s}{q_{max}} \cdot \Psi_w^b - \frac{p_{bid}^s}{p_{max}} \cdot (1 - \Psi_w^b)$, where $q_{max} \in Q$ is the maximum quality of good g in the market and $p_{max} \in P$ is the maximum price of good g with quality q_{max}. Let S_r^b, S_{nr}^b and S_{dr}^b be the set of reputable, non-reputable and disreputable sellers to buyer b, respectively. According to definitions 5 and 6, $S_r^b = \{s \in S \mid r_\Psi^b(s) \geq \Theta_\Psi^b\}$, $S_{nr}^b = \{s \in S \mid \theta_\Psi^b < r_\Psi^b(s) < \Theta_\Psi^b\}$, $S_{dr}^b = \{s \in S \mid r_\Psi^b(s) \leq \theta_\Psi^b\}$.

There are three possibilities, If $S_r^b \neq \phi$, buyer b attempts at selecting sellers among reputable ones that maximize the estimator function E^b. We denote these sellers as $\tilde{S} = \left\{ s \in S_r^b \middle| E^b = \max_{s \in S_r^b} E^b \right\}$. But if $S_r^b = \phi$, it means that there is no reputable seller to buyer b. In this situation, buyer b attempts to select sellers among non-reputable ones that maximize E^b. We denote these sellers as $\tilde{S} = \left\{ s \in S_{nr}^b \middle| E^b = \max_{s \in S_{nr}^b} E^b \right\}$. At last, if $S_r^b = \phi$ and $S_{nr}^b = \phi$, it means that all sellers are disreputable to buyer b. In this situation, buyer b attempts to select sellers among disreputable ones that maximize E^b. We denote these sellers as $\tilde{S} = \left\{ s \in S_{dr}^b \middle| E^b = \max_{s \in S_{dr}^b} E^b \right\}$. Now, buyer b chooses all the most reputable sellers among $\tilde{S}$. We denote these sellers as $S^* = \left\{ s \in \tilde{S} \middle| r^b(s) = \max_{s \in \tilde{S}} r^b(s) \right\}$.

Now, buyer b selects a seller $s^* \in S^*$, randomly. Buyer b announces seller s^* and pays him. After receiving the good g from seller s^*, buyer b updates the reputation of seller s^* on quality and price using reinforcement learning.

Assume that buyer b examines the real quality of the good g and finds quality $\hat{q}$ for good g delivered by seller s^*. Buyer b updates the reputation of seller s^* on quality using reinforcement learning by $r_q^b(s^*) \leftarrow r_q^b(s^*) + \lambda_q^b \cdot \left(1 - r_q^b(s^*)\right)$. Where $\lambda_p^b = \Psi_w^b \cdot RD_q \mathbf{1}_{[RD_q \geq 0]} + (1 - \Psi_w^b) \cdot RD_q \mathbf{1}_{[RD_q < 0]}$ is personality-based reputation impact factor for quality. In which $RD_q = (\hat{q} - q_{dem}^b)/(q_{max} - q_{dem}^b) \mathbf{1}_{[\hat{q} \geq q_{dem}^b]} + (\hat{q} - q_{dem}^b)/(q_{dem}^b - q_{min}) \mathbf{1}_{[\hat{q} < q_{dem}^b]}$ is relative deviation of quality and q_{dem}^b is buyer b's demanded quality of good g and $q_{min} \in Q$ is the minimum quality of good g in the market. If $RD_q \geq 0$, it means that seller s^* offers good g with a quality better than or equal to what the buyer b demanded for quality of good g. Therefore, as buyer b's personality score grows up, λ_q^b increases and consequently he adds more amount to the previous reputation

[4]. Seller Relative Profit

of seller s^* and vice versa. On the other hand, if $RD_q < 0$, it means that seller s^* offers good g with a quality lower than what the buyer b demanded for quality of good g. Therefore, as buyer b's personality score declines, λ_q^b decreases and consequently he subtracts more amount from the previous reputation of seller s^* and vice versa.

Buyer b updates the reputation of seller s^* on price using reinforcement learning,

$$r_p^b(s^*) \leftarrow r_p^b(s^*) + \lambda_p^b \cdot \left(1 - r_p^b(s^*)\right),$$

where

$$\lambda_p^b = \Psi_w^b \cdot RD_p \mathbf{1}_{[RD_p \geq 0]} + \left(1 - \Psi_w^b\right) \cdot RD_p \mathbf{1}_{[RD_p < 0]}$$ is personality-based reputation impact factor for price. In which,

$$RD_p = \left(p_{dem}^b - p_{bid}^{s^*}\right)/\left(p_{dem}^b - p_{min}\right)\mathbf{1}_{\left[p_{dem}^b \geq p_{bid}^{s^*}\right]} + \left(p_{dem}^b - p_{bid}^{s^*}\right)/\left(p_{max} - p_{dem}^b\right)\mathbf{1}_{\left[p_{dem}^b < p_{bid}^{s^*}\right]}$$

is relative deviation of price and p_{dem}^b is buyer b's demanded price of good g and $p_{min} \in P$ is the minimum price of good g with quality q_{min} in the market. If $RD_p \geq 0$, it means that seller s^* offers good g with a price lower than or equal to what the buyer b demanded for price of good g. Therefore, as buyer b's personality score grows up, λ_p^b increases and consequently he adds more amount to the previous reputation of seller s^* and vice versa. On the other hand, if $RD_p < 0$, it means that seller s^* offers good g with a price higher than what the buyer b demanded for price of good g. Therefore, as buyer b's personality score declines, λ_p^b decreases and consequently he subtracts more amount from the previous reputation of seller s^* and vice versa. After updating $r_q^b(s^*)$ and $r_p^b(s^*)$, buyer b updates the general reputation of s^* based on his reputation by $r_\Psi^b(s^*) = \Psi_w^b \cdot r_q^b(s^*) + \left(1 - \Psi_w^b\right) \cdot r_p^b(s^*)$. Finally, If $\left(s^* \notin S_r^b\right)$ and $\left(r_\Psi^b(s^*) \geq \Theta_\Psi^b\right)$, buyer b moves s^* to S_r^b. So, seller s^* will be considered as a reputable seller by buyer b in the next purchase. If $\left(s^* \notin S_{nr}^b\right)$ and $\left(\theta_\Psi^b < r_\Psi^b(s^*) < \Theta_\Psi^b\right)$, buyer b moves s^* to S_{nr}^b. So, seller s^* will be considered as a non-reputable seller by buyer b in the next purchase. If $\left(s^* \notin S_{dr}^b\right)$ and $\left(r_\Psi^b(s^*) \leq \theta_\Psi^b\right)$, buyer b moves s^* to S_{dr}^b. So, seller s^* will be considered as a disreputable seller by buyer b in the next purchase.

c. Weight vectors' refining Algorithm

Assume that the buyer b buys the good g from the seller s. As described about transactions 11 and 12 in figure 1, the buyer b announces to MMA that the good g has been bought from the seller s. After each succeeded transaction, MMA calculates the mean of each personality factor according to the all succeeded transaction for sellers and buyers, separately and then assigns particular weight to each factor of OCEAN model of personality. Suppose that n purchases have been accomplished successfully until now and consider the personality mean vector $\overline{\Psi^b} = \left(\overline{\psi_1^b}, \overline{\psi_2^b}, \overline{\psi_3^b}, \overline{\psi_4^b}, \overline{\psi_5^b}\right)$ representing the mean scores of five factors for those buyers who purchase, where $\overline{\psi_i^b} = \sum_{j=1}^{n} \psi_i^{b_j}/n$.

In which, $\psi_i^{b_j}$ is the score of i'th personality factor for the buyer who buys a good in j'th succeeded purchase transaction. Each component of the weight vector $W^b = \left(w_1^b, w_2^b, w_3^b, w_4^b, w_5^b\right)$ is refined and updated by $w_i^b = \overline{\psi_i^b}/\sum_{k=1}^{5} \psi_k^b$. Similarly, MMA refines and updates weight vector W^s by replacing b with s in what described above for buyer.

III. Experimental Results

We have implemented our proposed model with Aglet, which is java based environment, for building mobile and stationary agents, considering 20 seller agents and 20 buyer agents in a simulated marketplace. It is supposed that buyers totally accomplish 2000 purchases in the market, and both seller and buyer are classified into four groups. The behavior of three first groups of sellers and buyers is based on our proposed model. Seller groups are defined as follows: Group S1 consists of 5 seller with a personality score lower through 0.45, Group S2 consists of 5 seller with a personality score between 0.45 and 0.55, Group S3 consists of 5 seller with a personality score 0.55 through highest, and Group S4 consists of 5 seller {s_15,s_16,…,s_19 } which do not model the reputation of buyers based on his personality. They start with a specified bid and then alter it based on buyers' requirements.

Similarly, buyer agent groups B1, B2 and B3 are defined by replacing S and s_i with B and b_iin above seller agent groups, respectively. Also, Group B4 consists of 5 buyer agents which do not model the reputation of sellers based on his personality.

The results of the experiment confirm that personality influences the buyer and seller agent's behavior in the market. This result is compatible with research marketing and personality. Table 7 contains the total number of purchases made by groups of buyers from sellers group.

TABLE VII
TOTAL NUMBER OF PURCHASES MADE BY GROUPS OF BUYERS FROM SELLERS GROUP

Group	S_1	S_2	S_3	S_4
B_1	59	92	263	86
B_2	21	99	364	16
B_3	5	33	452	10
B_4	9	101	313	77

Table 8, shows the total and average sales of different groups of sellers. As this table shows, the minimum number of sales made by group $S_1$of sellers whose personality scores is lower through 0.45. They attempt to cheat the buyer agents and based on their low personality score, they offer high

quality goods and deliver the goods with really low quality. It means that they exaggerate about their goods without any responsibility. Results show that, buyers do not continue their communication with them and each buyer purchases the good from them only in the beginning. The reputation of these sellers becomes lower than buyer's personality-based disreputable threshold and they cannot be selected again by buyers in their future purchases.

The maximum number of sales are made by group S_3 which consists of sellers with a personality score of 0.55 through highest. Decreasing of personality-based percent of profit is one of the important factors that sellers can promote for their own reputable buyers. Sellers of group S_3, apply this marketing strategy to increase their profit and number of customers.

TABLE VIII
TOTAL AND AVERAGE NUMBER OF SALES BY FOUR GROUPS OF SELLERS

Group	S_1	S_2	S_3	S_4
Total number of sales	94	325	1392	189
Average number of sales	18.5	65	278.4	37.8

IV. CONCLUSION

In this paper we proposed a model based on weighted OCEAN model of personality for buyer and seller agents in multi agent-based electronic marketplaces. Four important factors: personality, reputation, quality, and price are considered in the model. Selling agents learn to maximize their benefits by adjusting goods' prices and quality based on their personality and more important considering discount for buyers based on their reputation. We showed that sellers who use the proposed model achieve more satisfaction in comparison with the others. Buyers also learn to purchase from the most reputable sellers based on their personality. We have investigated this fact that personality of seller and buyers is important factor in business, so that Sellers with high score of personality earn more benefits and construct better reputation for themselves among buyers reputation compared to the others. Buyer also with high score of personality purchase more new goods and more expensive goods relative to buyers with low score of personality.

REFERENCES

[1] C. Lenz, «e-Marketplaces: How are they changing your business environment». Gartner Symposium ITXPO 2000, Insight for the connected world. Walt Disney World, Orlando, Florida, USA. 16-20 October 2000.

[2] G. Weiss, A Modern Approach to Distributed Artificial Intelligence. The MIT Press Cambridge, 1999.

[3] N. Archer and J. Gebauer, Managing in the Context of the New Electronic Marketplace, 2000. Proceedings 1st World Congress on the Management of Electronic Commerce, Hamilton, Ontario, Canada, January pp. 19 – 21.

[4] N. Russ, E-marketplaces: New Challenges for Enterprise Policy, Competition and Standardisation. eEurope go Digital. Workshop Report, Brussels, 23-24 April 2001.

[5] O. Roozmand, M. A. Nematbakhsh, and A. Baraani, An Electronic Marketplace Based on Reputation and Learning, Journal of theoretical and applied electronic commerce research, Vol. 2, Issue 1, pp. 1-17, 2007.

[6] T. Zhang and D. Zhang, Agent-based simulation of consumer purchase decision-making and the decoy effect, Journal of Business research, vol. 60, No. 8, pp. 912-922, 2007. http://dx.doi.org/10.1016/j.jbusres.2007.02.006

[7] A. Barzegar, A. Jahanbani, and O. Roozmand, Openness, Conscientiousness and Stingy for Buyer and Seller Agents in Electronic Marketplace, International journal of Computer Theory and Engineering, Vol. 2, No. 3, pp. 358-363, 2010.

[8] R. Santos, G. Marreiros, C. Ramos, J. Neves, and J. Bulas, Multi-agent Approach for Ubiquitous Group Decision Support Involving Emotions. LNCS, 4159, pp. 1174 – 1185, 2006. http://dx.doi.org/10.1007/11833529_118

[9] S. Sarker, T. K. Bose, M. Palit, E. Haque, Influence of personality in buying consumer goods-a comparative study between neo-Freudian theories and trait theory based on Khulna region, International Journal of Business and Economics Research, 2(3), pp. 41-58, 2013. http://dx.doi.org/10.11648/j.ijber.20130203.12

[10] B. Nagarkoti, Factors influencing consumer behavior of smartphone users. Degree Thesis International Business (BBA), 2009.

[11] G. Marreiros, R. Santos, C. Ramos, J. Neves, and J. Bulas, A Multi-agent System that Simulates Group Decision Processes Considering Emotional and Argumentative Aspects. AAAI Spring Symposium on Emotion, Personality and Social Behaviour, Stanford, pp. 88-95, 2008.