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# AN ADAPTIVE SUPPLIER SELECTION MECHANISM IN E-PROCUREMENT MARKETPLACE

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## ABSTRACT

*B2B e-commerce has fundamentally changed the way in which an organization purchases goods/service. Nowadays, the adoption of e-procurement, which means the electronic acquisition of goods/service, has been prevalent in supply chain management. A variety of supplier selection models have been developed in supply chain management literature. In this research, an adaptive supplier selection mechanism is proposed to help buyers evaluate suppliers in an e-marketplace. A Multi-Agent System simulation package of Repast is used to create a realistic environment where different kinds of suppliers and buyers equipped with the proposed selection model can interact so as to study the performance of the proposed selection model. We evaluate three supplier selection models and find that our proposed model outperforms the other two in terms of robustness and performance.*

**KEYWORDS:** Multi-agent systems, Multiple criteria analysis, Simulation, Supplier Quality, Supplier Selection

## INTRODUCTION

B2B e-commerce has fundamentally changed the way in which an organization purchases goods/service. Nowadays, the adoption of e-procurement, which means the electronic acquisition of goods/service, has been prevalent in supply chain management. There are different types of e-procurement systems on the market. For example, public e-markets such as W.W. Grainger, Ariba; consortia-based e-markets such as E2Open in the electronic industry, or private e-markets run by either supplier or buyer (e.g., Motorola, or GE). B2B Marketplaces can also be classified as horizontal or vertical in terms of materials transacted in the e-procurement system. Horizontal marketplaces involve buyers or suppliers from different industries exchanging maintenance, repairs and operations (MRO) materials; while vertical marketplace involve buyer and suppliers from same industries exchanging direct materials such as strategic components or commodity products. In this paper, we are interested in studying buyer-side marketplace where the buyer needs to purchase commodity products or MRO materials from multiple suppliers. Because suppliers are heterogeneous, we aim to design an adaptive supplier selection mechanism to meet the buyer's needs.

Supplier selection has been extensively studied in supply chain management. Criteria considered in supplier selection are critical to the success of supply management. In the past, factors such as price, delivery, quality and service were valued in supplier selection. However, due to increased supply chain complexity and uncertainty, price is no longer the most critical factor (Wu and Weng, 2010), but other factors such as on-time performance, supply flexibility, product design collaboration capability, supplier viability and low-carbon footprint (Govindan & Sivakumar, 2016) also need to be assessed in today's supply chain environment. Based on supply chain operations reference (SCOR) model developed by supply chain council (SCC), Huang and Keskar (2007) comprehensively classified performance metrics for supplier selection into seven categories, namely reliability, responsiveness, flexibility, cost and financial, assets and infrastructure, safety, and environment. Sen et al. (2008) developed a hierarchical criteria structure for supplier selection, which includes qualitative and quantitative attributes such as cost, quality, service, reliability, management and organization, and technology. Pan & Choi (2016) proposed an two-phase agent-based negotiation model to study a fashion supply chain, where due-date and price are two criteria to find Pareto solution under cooperative and competitive phases. In recent years, due to the

environmental and sustainability awareness, green criteria has also been incorporated into the decision of supplier selection (Genovese et al. 2013, Jain et al. 2016)

## LITERATURE REVIEW

A variety of supplier selection models have been developed in supply chain management literature. Lee and Ou-Yang (2007) reviewed supplier selection methodologies till 2007. These methodologies include mixed integer programming, simulation, experiment, fuzzy programming, genetic algorithm and agent technology, analytic hierarchy process (AHP), etc. Later on, Ravindran et al. (2010) summarized three clusters of supplier selection models: the first cluster is multi-objective mathematical programming methods; the second cluster is game theoretic methods and the third cluster is the applications of artificial intelligence on supplier selections. In their invited review, Ho et al. (2010) surveyed two different approaches to supplier evaluation and selection: individual approaches and integrated approaches. Individual approaches includes data envelopment analysis, mathematical programming, analytic hierarchy process, analytic network process, fuzzy set theory, simple multi-attribute rating technique (SMART), and genetic algorithm. Integrated approaches includes integrated AHP approaches, integrated fuzzy approaches, other approaches such as integrated ANN and case-based reasoning (CBR), integrated ANN and GA, integrated DEA and SMART. For example, Bai and Sarkis (2010) integrated sustainability into supplier selection process, where they adopted multi-stage, multi-method approach and utilized grey system and rough set theory to evaluate supplier selection decisions. Based on basic data envelopment analysis (DEA), Wu and Blackhurst (2009) proposed an augmented DEA methodology to rank suppliers. In this enhanced model, they incorporated virtual standards and the weight constraints. Che (2010) constructed a mathematical model for assembly sequence planning (ASP) multi-period supplier selection problem in order to minimize the integrated criteria, and a hybrid heuristic algorithm, referred to as guided-Pareto genetic algorithm (Gu-PGA) was developed to find satisfactory solution. Wu et al. (2007) applied bootstrap simulation technique to evaluate supplier's process capability indices, and compared performance among different bootstrap methods and supplier selection power. Sevkli (2010) proposed a fuzzy technique known as ELECTRE for supplier selection decision drawing on a real Turkish industry case. Ghorbani et al. (2013) integrated quality management tool into supplier selection and proposed a three-phase approach based on the Kano model and fuzzy MCDM. Yu et al. (2017) also considered the synergy effect affecting the choice of supplier selection. They proposed an agent-based negotiation model to automate multi-product supplier

selection problem. Other most research has combined the above mentioned methodologies.

One common limitation of the models mentioned above is the decisions cannot be dynamically adjusted based on the updated information, which is pivotal in today's e-business environment. Therefore, in this paper we are trying to design a dynamic online multi-criterion supplier selection mechanism, by which buyers can dynamically update the due parameters, adapt to the changing environment and obtain the decent outcome based on the on-going performance of the suppliers in term of quality and flexibility.

We have borrowed the same concept and design of the multi-agent system used in You and Sikora (2011) and applied it to a different context of supplier selection in this paper. Instead of sellers with feedback ratings in the traditional consumer markets as in You and Sikora we have suppliers in this new context who supply with varying quality and flexibility.

## **SUPPLIER EVALUATION IN E-PROCUREMENT ENVIRONMENT**

In contrast to traditional procurement, how to evaluate and select suppliers in the e-procurement system is more challenging due to more uncertainty and risk involved in the whole procurement process. Typically, buyer's online requisitions are generated by applications like inventory, work in process (WIP), advanced supply chain planning and order management system. Afterwards, an online request for quotation (RFQ) is announced, and eligible suppliers respond to the RFQ, this is referred to as quotations. One supplier is then selected to transact business from all the quotations. Among all criteria of supplier selection, price is the easiest one for suppliers to comply with and thus price has the lowest importance (Bottani and Rizzi, 2005); however other criteria such as quality or flexibility is not observed by the buyer till the product is delivered, and may cause significant cost to the buyer. Therefore in this paper, we assume the price is not a criterion considered in the evaluation process. In other words, all eligible suppliers in the e-procurement system offer the same price based on spot market price, which is especially true for MRO materials. Instead, we are interested in two supplier criteria in the B2B e-procurement environment, 1) product quality; 2) supplier flexibility. Quality of the product criteria in the e-procurement system is usually the quality of conformance, i.e., the degree to which goods or service conform to the specification by supplier. Supply flexibility refers to the supplier's ability to respond to buyer's changing requirements of purchased materials in terms of volume, mix and delivery date (Tachizawa and Gimenez, 2009). We also assume the buyer periodically purchases

standard products, and demand is stochastic. After each transaction, the buyer dynamically updates supplier performance and establishes an adaptive supplier selection mechanism. Supplier selection over the Internet can reduce buyers' costs of search, communication and evaluation for standard products (Barua et al. 1997). However, how to manage supply risk in e-procurement environment is a challenge. Specifically, in this research, we assume all suppliers respond to RFQ or post the same bidding price (Posted value, or  $PV$ ); however when they come to deliver the service/goods, two attributes of supplier section varies. The first is the product quality. When suppliers deliver the service/goods, quality could be either high or low. We use delivered value ( $DV$ ) to measure the intrinsic quality of the delivered goods. The difference between  $DV$  and  $PV$  ( $DV - PV$ ) is used to measure the supply uncertainty in terms of quality. The buyer will be better off if the value of  $DV - PV$  is positive, or will be highly likely to incur a loss if the value  $DV - PV$  is negative. Therefore when a buyer makes decision on supplier selection, this value difference is used as an attribute to evaluate the performance of different suppliers.

The second attribute is supply flexibility, which measures the supplier's ability to respond to changes in demand or other requirements such as delivery time. Similarly, suppliers' flexibility could be high or low. High supply flexibility means the supplier is more responsive and agile to meet the needs of the buyers, which is critical for managing supply chain risks or exceptions.

There can be other important attributes that can influence the selection process; we can also include these attributes in our proposed model as in Fig.1. For simplicity purpose, we will only consider the quality and flexibility attributes in the following simulation.

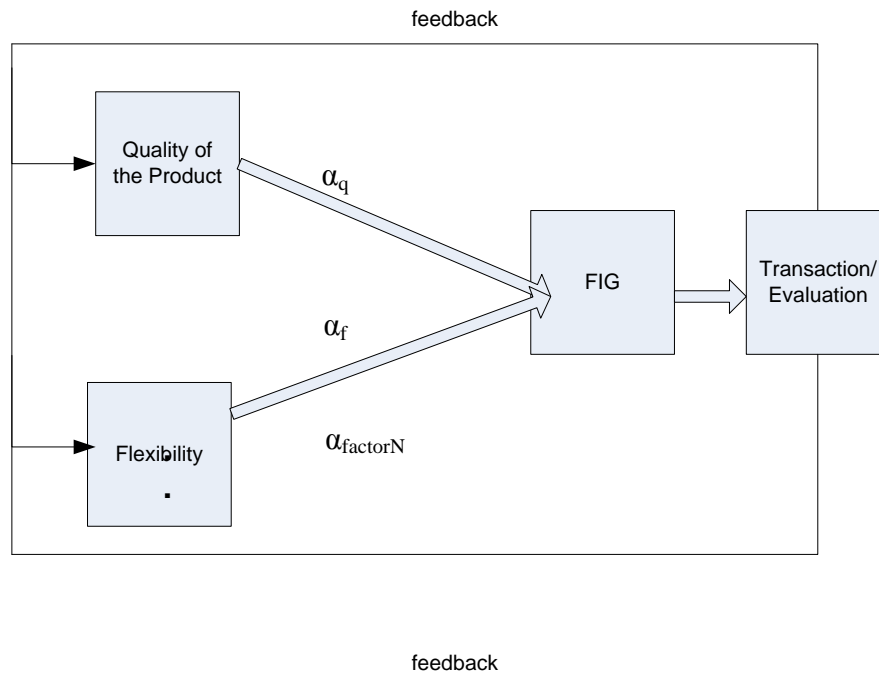


Figure 1: Dynamic supplier selection model based on quality and flexibility

## SIMULATION DESIGN

In this study, Multi-Agent System simulation package of Repast J (North, Collier, & Vos, 2006) is adopted to build a realistic E-Procurement environment where different kinds of suppliers and buyers equipped with the proposed selection model can interact with each other so as to study the performance of the proposed selection model.

This e-procurement environment is composed of supplier agents (suppliers), buyer agents (buyers), a Bulletin Board (BB) and a computational module. The suppliers and buyers can interact with each other. The BB is the place where a buyer announces RFQ, suppliers respond to RFQ and the buyer posts the data of the transaction result with the selected supplier. The computational module does the necessary computations using data from the BB for a buyer to select a supplier in an upcoming transaction. Numerous iterations of above-mentioned interactions go on in the multi-agent system to simulate the functioning of an e-procurement environment. Each iteration is made of several steps. First, buyers generate demand following a demand equation and announce the RFQ via the BB; then the

suppliers responds to the RFQ on the BB; after that each buyer selects a supplier based on the proposed selection model and the prior performance of the supplier to initiate transactions with the selected supplier; and then the supplier reveals the results of the transaction to the buyer; finally the buyer posts the data of the transaction result via the BB. Within each iteration the sequence of transactions is inconsequential; since only the data of transactions from fifty preceding iterations are utilized to select the due suppliers.

To simulate a more diverse set of suppliers in the selection environment, the following four kinds of suppliers are considered in simulation: Q0.8F0.8 suppliers, Q0.6F0.6 suppliers, Q0.4F0.4 suppliers, and Q0.2F0.2 suppliers. The notation of these suppliers indicates their propensity to provide high quality and highly flexible service. For example, Q0.8F0.8 suppliers provide high quality service 80% of the time and highly flexible service 80% of the time.

To quantify the quality and flexibility of a transaction from both the buyer's and supplier's perspective, we model the intrinsic quality value of the transacted goods based on two terms: delivered quality value (DV) and posted quality value (PV); and the intrinsic flexibility value of the transaction based on two terms: the mean respond rate of the due industry and the actual respond rate of a transaction. The PV is similar to the listed price of an item but in our model it captures the expected "value" in quality that is being offered by the supplier. The DV is the actual quality "value" delivered to the buyer at the end of the transaction and models the satisfaction of the buyer with the product's quality. When a supplier is cooperative in term of quality, the supplier provides a DV that is equal to or more than the corresponding PV. In the simulation experiments, the DV is drawn from a normal distribution and keeps concealed from the buyer until after the transaction is finished. The mean of DV for high-quality service is set to be greater than the PV and the mean of DV for low-quality service to a value less than the PV. When a supplier is cooperative in term of flexibility, the supplier will provide the goods with a respond rate (RR) greater than the industry mean respond rate. In our simulation experiments, the respond rate is drawn from a normal distribution and also remains unknown to the buyer until after the transaction is done.

When designing the simulation framework, we assume the buyer's demand is stochastic, which follows  $AR(1)$  time series process (e.g., Box et al. 1994):



$$d_t = \phi_0 + \phi d_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_0^2), \quad |\phi| < 1, \quad (1)$$

where  $d_t$  is the demand at period  $t$ ,  $\phi$  is a constant,  $\varepsilon_t$  is the white noise.

The buyer in our simulation experiments uses the proposed model to calculate each supplier's forecasted integrated gain (*FIG*) from both quality and flexibility factors of previous transactions. Then a buyer selects a supplier based on the calculated suppliers' *FIG* values. In the real world other factors might also affect the selection of a supplier, such as, reliability, price, safety and reputation, etc. For instance, a buyer might be willing to buy from a supplier with less than the highest *FIG* if the item is being sold with more attractive incentive provided by the supplier, such as discount, safety and/or reliability. Since our focus in this paper is the use of the proposed supplier selection model, we model this trade-off between the *FIG* of a supplier and other factors by using a Boltzmann distribution (Kaelbling, Littman, & Moore, 1996) for selecting a supplier. Boltzmann distribution is widely used in Reinforcement Learning techniques like Softmax (Sutton, R.S., & Barto, A.G., 1998), and it allocates a probability for each supplier as follows:

$$\Pr(s_j) = e^{FIG(s_j)/\tau} / \sum_{i=1}^n e^{FIG(s_i)/\tau} \quad \text{where } \tau > 0, \quad (2)$$

where  $\Pr(s_j)$  is the probability of selecting the supplier  $s_j$ ,  $FIG(s_i)$  is the *FIG* value of supplier  $s_i$ , and  $\tau$  is the temperature constant. With this method, a buyer is able to both exploit its knowledge about the suppliers' *FIG* values and explore potential good suppliers in terms of all other factors except for quality and flexibility. At very high temperatures the method approaches a random search i.e., all the suppliers are selected with equal probability. At very low temperatures the method approaches a greedy search i.e., only the supplier with the best *FIG* value is selected. Thus the temperature constant is controlled to model the above-mentioned trade-off between *FIG* value and other factors. For example, a buyer who is willing to buy in favor of factors other than quality and flexibility from suppliers with sub-par *FIG* value would set the temperature constant at a higher value compared to a quality-and-flexibility favoring buyer who prefers buying from only well-known good suppliers in terms of quality and flexibility. In the experiments, buyers' and suppliers' gains are used to measure the performance of the proposed model in the selection environment. The buyer's gain includes two parts, which are the gain from quality ( $GB^q$ ) and gain from flexibility ( $GB^f$ ).  $GB^q$  in a transaction is defined as the product of the demand and the difference between the DV and the PV:

$$GB_t^q = (DV_t - PV_t)d_t, \quad (3)$$

And the  $GB^f$  in a transaction is defined as:

$$GB_t^f = \begin{cases} c_b(r - \bar{r})^2 PV * d_t & \text{if } r - \bar{r} \geq 0 \\ -c_b(r - \bar{r})^2 PV * d_t & \text{if } r - \bar{r} < 0 \end{cases}, \quad (4)$$

where  $c_b$  is the coefficient of the loss function for the buyer and  $r$  is the respond rate of the supplier in a transaction and  $\bar{r}$  is the industry mean respond rate. When  $r$  is greater than  $\bar{r}$ , it means the supplier's respond rate is higher than the industry average, so the buyer is gaining on the transaction due to higher than average flexibility it receives. Like the buyer, the supplier's gain ( $GS$ ) also includes the two parts, the gain from quality ( $GS_t^q$ ) and the gain from flexibility ( $GS_t^f$ ). The gross profit of a supplier from quality factor is defined as  $mPV$ , where  $m (<1)$  is the profit margin. The gain for a supplier from quality factor depends on the  $DV$ , the demand in transactions and is given by:

$$GS_t^q = [mPV + (PV - DV_t)] * d_t. \quad (5)$$

A supplier can therefore gain more by providing a  $DV$  that is less than the  $PV$ . A supplier can gain less than the gross profit by providing a  $DV$  that is better than the  $PV$ .

And  $GS^f$  in a transaction is defined as :

$$GS_t^f = \begin{cases} -c_s(r_t - \bar{r})^2 PV_t * d_t & \text{if } (r_t - \bar{r}) \geq 0 \\ c_s(r_t - \bar{r})^2 PV_t * d_t & \text{if } (r_t - \bar{r}) < 0 \end{cases}, \quad (6)$$

where  $c_s$  is the constant of the loss function for the supplier and  $r$  is the respond rate of the supplier in a transaction and  $\bar{r}$  is the industry mean respond rate. When  $r$  is greater than  $\bar{r}$ , the supplier is losing on the transaction, by providing more flexibility with a respond rate higher than the industry mean respond rate. We assume that no supplier would conduct a transaction that incurs a loss, i.e.,

$$GS_t = GS_t^q + GS_t^f > 0. \quad (7)$$

The  $DV_t$  is drawn from a normal distribution with a standard deviation of  $\square$  and a mean of  $(1 + g)PV$  for high quality service and a mean of  $(1 - g)PV$  for low quality

service, where  $g (<1)$  is a constant. Since with more than 95% of the probability, the actual value of  $DV_t$  falls within two standard deviations of the mean, the maximum and minimum values of  $DV_t$  can be approximated as:

$$DV_{\max} = (1 + g)PV + 2\sigma, \quad (8)$$

$$DV_{\min} = (1 - g)PV - 2\sigma. \quad (9)$$

The respond rate ( $r_t$ ) is drawn from another normal distribution with a standard deviation of  $\sigma'$  and a mean of  $(1 + h)\bar{r}$  for more flexible service and a mean of  $(1 - h)\bar{r}$  for less flexible service, where  $h (<1)$  is a constant. Since with more than 95% of the probability the actual value of  $r_t$  falls within two standard deviation of the mean, the maximum and minimum value of  $r_t$  can also be approximated as:

$$r_{\max} = (1 + h)\bar{r} + 2\sigma', \quad (10)$$

$$r_{\min} = (1 - h)\bar{r} - 2\sigma'. \quad (11)$$

We also assume that when high-quality service is provided the actual  $DV_t$  is never less than the  $PV$  and when low-quality service is provided, the actual  $DV_t$  is never greater than the  $PV$ . Similarly, when more flexible service is provided the actual  $r_t$  is never less than the  $\bar{r}$  and when less flexible service is provided the actual  $r_t$  is never greater than the  $\bar{r}$ , i.e.,

$$(1 - g)PV + 2\sigma < PV < (1 + g)PV - 2\sigma, \quad (12)$$

$$(1 - h)\bar{r} + 2\sigma' < \bar{r} < (1 + h)\bar{r} - 2\sigma'. \quad (13)$$

By Eq. (12), we get,

$$\sigma < \frac{gPV}{2}. \quad (14)$$

By Eq. (13), we get,

$$\sigma' < \frac{h\bar{r}}{2}. \quad (15)$$

When  $DV_t$  is highest and  $r_t$  is greater than  $\bar{r}$ , the LHS of Eq.(7) has the smallest value. Combining equations (6), (7), (8) and (10) we get:

$$(r_t - \bar{r})^2 < \frac{(m-g)PV - 2\sigma}{c_s PV}, \quad (16)$$

$$\bar{r} - \sqrt{\frac{(m-g)PV - 2\sigma}{c_s PV}} < r_t < \bar{r} + \sqrt{\frac{(m-g)PV - 2\sigma}{c_s PV}}. \quad (17)$$

Since  $(r_t - \bar{r})^2 \geq 0$ , it implies that  $(m-g)PV \geq 2\sigma$ , i.e.,

$$\sigma \leq \frac{(m-g)PV}{2}. \quad (18)$$

Since  $\square\square > 0$ , it also implies that  $m > g$ . The above equations are used to determine values for the constants  $m$  and  $g$ , and for the standard deviations  $\square\square$  and  $\square'$ . Using the maximum and minimum values of  $DV_t$  from equations (8) and (9) we further get the following inequality for the value of  $DV_t$ :

$$(1-g)PV - 2\sigma \leq DV_t \leq (1+g)PV + 2\sigma. \quad (19)$$

From (6), we have

$$(GS_t^f)_{\max} = c_s((1-h)\bar{r} - 2\sigma' - \bar{r})^2 PV * d_t, \text{ when } r_t = (1-h)\bar{r} - 2\sigma' \quad (20)$$

and,

$$(GS_t^f)_{\min} = -c_s((1+h)\bar{r} + 2\sigma' - \bar{r})^2 PV * d_t, \text{ when } r_t = (1+h)\bar{r} + 2\sigma' \quad (21)$$

Combining equations(5), (7), (8) and (21) we get,

$$\sigma \leq \frac{(m-g)PV - c_s(h\bar{r} + 2\sigma')^2 PV}{2}. \quad (22)$$

In our simulation, all the parameter values were determined by either complying with standard simulation practices or conducting informal sensitivity analysis. For example, in order to find the temperature constant  $\tau$  in Boltzmann's distribution (Eq. 2), which controls the trade-off between the *FIG* value and other factors in selecting suppliers, we applied a sensitivity analysis with three values for  $\tau = 0.02$ , 0.2, and 2 and determined that  $\tau = 0.2$  resulted in the best trade-off.

There were 24 buyers, and 8 suppliers, of which 2 suppliers of each type (Q0.8F0.8, Q0.6F0.6, Q0.4F0.4, Q0.2F0.2) in all of our simulation experiments. And the PV of the item was set at 8.0. The profit margin  $m$  was set at 0.3; the constant  $g$  was set at 0.2; the constant of  $h$  was set at 0.2; the average respond rate of  $\bar{r}$  was set at 0.5. The  $c_b$  and  $c_s$  were set at 0.5 for Eqs. (4) and (6), respectively. The standard deviation ( $\sigma$ ) for the respond rate of the supplier was set at 0.045 and  $\bar{r}$  was set to 0.5 to satisfy Eq.(15). The standard deviation ( $\sigma$ ) for the DV for the item was set at 0.295 to satisfy Eqs.(14),(18),(22). The  $\phi_0$  and  $\phi_1$  in Eq. (1) was set at 20 and 0.2, respectively.

When learning is adopted, a buyer selects suppliers based on these suppliers performance in the previous immediate  $n$  periods in terms of  $GB_t^q$  and  $GB_t^f$ . For each supplier, the forecast integrity gain value (FIG) is calculated first, and then Boltzman algorithm (Kaelbling, Littman & Moore, 1996) is adopted to select a supplier. Boltzman algorithm assigns high probability to suppliers with higher FIG values. The FIG at tick  $t$  in term of  $GB_t^q$  and  $GB_t^f$  is calculated as follows:

$$FIG(t) = \frac{a_q \cdot \frac{\sum_{i=t-n}^{t-1} NormalizedGB_q}{volume} + a_f \cdot \frac{\sum_{i=t-n}^{t-1} NormalizedGB_f}{volume}}{a_q + a_f}, \quad (23)$$

where  $\sum_{i=t-n}^{t-1} NormalizedGB_q$  is the sum of normalized gain of all buyers in term of quality from the evaluated supplier in the previous  $n$  periods;  $\sum_{i=t-n}^{t-1} NormalizedGB_f$  is the sum of normalized gain of all buyers in terms of flexibility from the evaluated supplier in the previous  $n$  periods; volume is the number of items traded between the evaluated supplier and all buyers in the previous  $n$  periods,  $a_q$  and  $a_f$  are the learnt coefficients for quality gain and flexibility gain parts, respectively.

The coefficients are learnt by a buyer using the following equation;

$$a_q(t+1) = a_q(t) + \eta_q \left( NormalizedGB_q(t) - \frac{\sum_{i=t-n}^{t-1} NormalizedGB_q}{volume} \right) \quad \text{and} \quad (24)$$

$$a_f(t+1) = a_f(t) + \eta_f \left( \text{NormalizedGB}_f(t) - \frac{\sum_{i=t-n}^{t-1} \text{NormalizedGB}_f}{\text{volume}} \right), \quad (25)$$

where  $\eta_q, \eta_f$  are the learning rates for  $a_q$  and  $a_f$ , respectively.  $\text{NormalizedGB}_q(t)$  and  $\text{NormalizedGB}_f(t)$  are the normalized quality gain and normalized flexibility gain of the buyer from the transaction between the evaluated supplier and the buyer at tick  $t$ , respectively. The following parameters and values are used in all the experiments:

Notation	Description	Value
m	Profit margin for supplier	0.3
g	The deviation control constant of DV	0.2
PV	Posted value of the item in unit in term of quality	8
DV	Delivered value of the item in unit in term of quality	
$\sigma$	STD of the DV	0.295
r	The respond rate in a transaction of the supplier	
$\bar{r}$	The average respond rate in the designated industry	0.5
h	The deviation control constant of the respond rate	0.2
$c_s$	The constant for the supplier's loss function	0.5
$\sigma'$	The STD of the respond rate of a supplier	0.045
$c_b$	The constant for the buyer's loss function	0.5
$\phi_0$	Constant in equation(1)	20
$\phi$	Constant in equation (1)	0.2
n	The number of immediate previous periods used to calculate FIG value	50

In next section we present the results of the simulation experiments testing the performance of the proposed selection model.

## RESULTS AND DISCUSSION

### BASE CASE

We first carry out simulation experiments comparing the following supplier selection models: Traditional, Static and Dynamic. In the Traditional model, which is the a benchmark the buyer checks whether the supplier selection in the previous

iteration improved its gain. If it did then it selects the same supplier. If it did not improve the buyer's gain then it randomly picks another supplier. On iteration 0 it picks a supplier randomly and picks the same supplier on iteration 1. From iteration 2 it follows the rule mentioned above. For the Static model, we use a fixed set of coefficients  $a_q$  and  $a_f$  to calculate FIG in eq. (23). For the Dynamic model, we use learning to dynamically adapt the coefficients  $a_q$  and  $a_f$  using eq. (24) and (25). The simulation is run for 1000 iterations and the average gain over the last 100 iterations is recorded. Each experiment is then repeated 10 times, and the average of those 10 runs is reported in the results.

The goal of an ideal supplier selection model should be to maximize the gains of buyers and suppliers who provide higher quality and flexibility, like Q0.8F0.8 suppliers. At the same time, it should also penalize the lower quality and flexible suppliers like Q0.4F0.4 and Q0.2F0.2 suppliers to discourage such suppliers from dominating the marketplace.

Table 1 presents the results comparing the relative performance of the three supplier selection models on the buyer gain as well as the different suppliers' gain. It shows that while the Static model is better than the Traditional model, the Dynamic model is the best in terms of improving the gains for the buyers and the suppliers with higher quality and flexibility while penalizing those suppliers with lower quality and flexibility. The table also gives the results of paired- $t$  test to show that all the improvements are statistically significant. The Dynamic model is able to increase the buyer's gain over the Traditional model by more than 500% while increasing it by more than 15% over the Static model. It increases the higher quality supplier's gain by more than 85% and 20% respectively over the Traditional and Static models. We plot the same results in figures 2 and 3 showing the relative improvement brought on by the Dynamic model over the traditional and static models on the buyer's gain and the high quality supplier (Q0.8F0.8). The error bars in the plot show the variability in the results. Figure 4 shows the same result for the lower quality supplier (Q0.2F0.2) demonstrating that the dynamic model is the best in penalizing lower quality suppliers.

Supplier Selection Models		Suppliers' Gain				
		Buyer's Gain	Q0.8F 0.8	Q0.6F 0.6	Q0.4F 0.4	Q0.2F 0.2
Traditional	Avg	47.76	244.15	308.51	370.72	411.27
	Std/Avg	7.51	0.83	0.76	0.63	0.53
Static	Avg	260.06	378.80	323.52	251.09	168.93
	Std/Avg	1.44	0.76	0.73	0.70	0.77
	Pw/Trade	<b>3.49E-05</b>	<b>2.49E-06</b>	n.s.	<b>3.10E-07</b>	<b>1.05E-09</b>
Dynamic	Avg	301.10	456.92	312.05	193.67	118.65
	Std/Avg	1.34	0.73	0.79	0.82	0.93
	Pw/Trade	<b>1.27E-06</b>	<b>2.08E-09</b>	n.s.	<b>6.43E-08</b>	<b>1.22E-11</b>
	Pw/Stat	<b>9.20E-02</b>	<b>4.06E-04</b>	n.s.	<b>4.98E-04</b>	<b>8.01E-05</b>

Table 1. Relative performance of different supplier selection models for base case

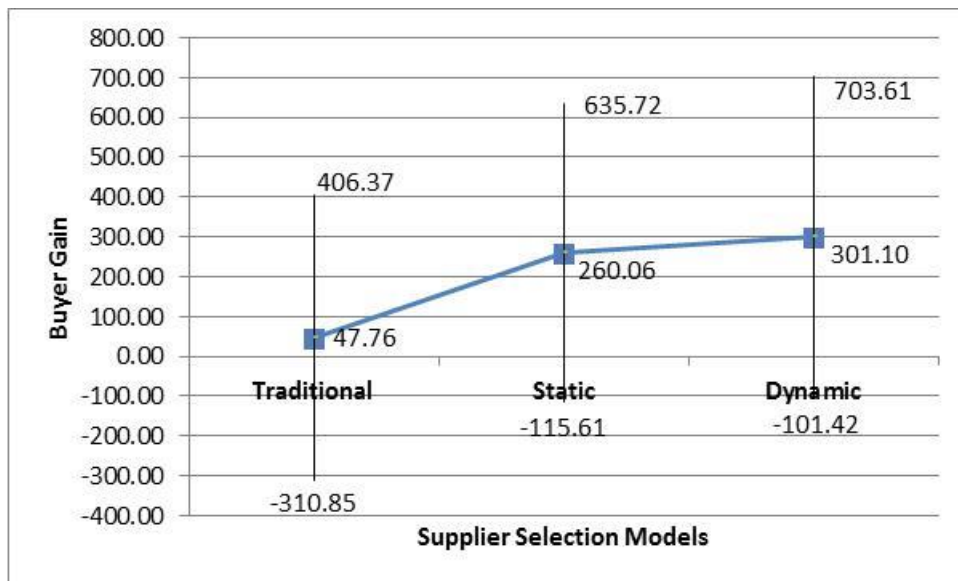


Figure 2. Performance of buyer's gain under base case



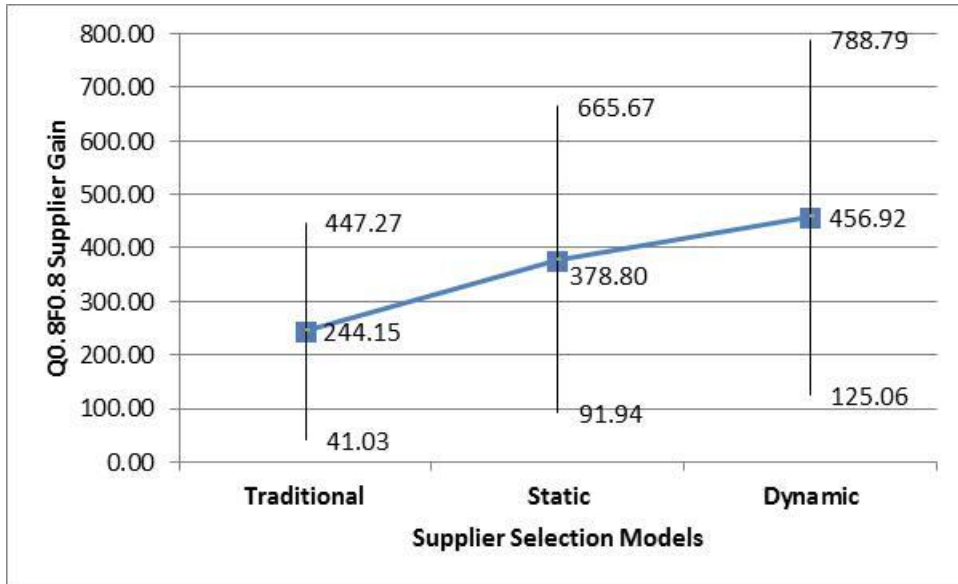


Figure 3. Performance of Q0.8F0.8 supplier's gain under base case

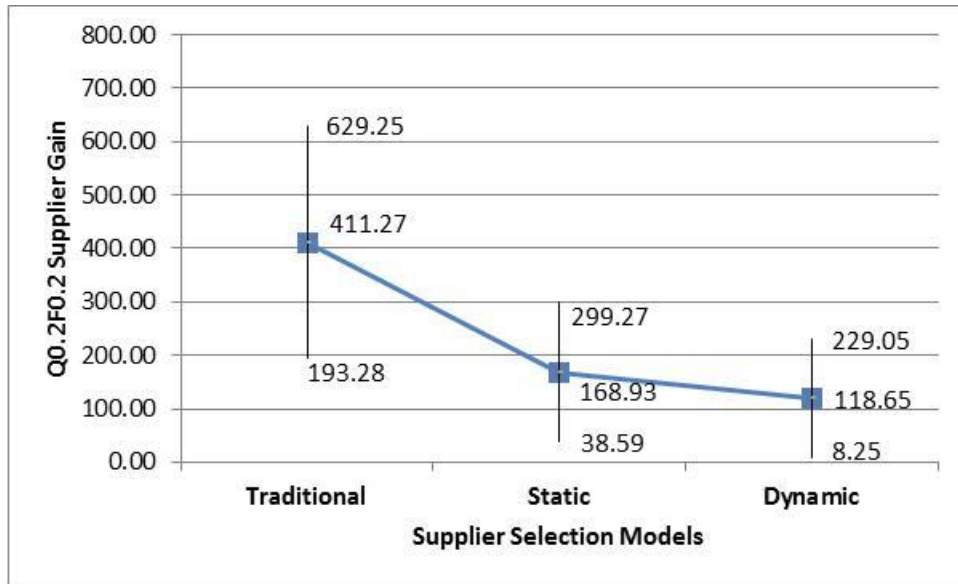


Figure 4. Performance of Q0.2F0.2 supplier's gain under base case

## SENSITIVITY ANALYSIS

For validity of the results and to ensure that the results are not an artifact of certain parameter values, we carried out sensitivity analysis of various parameters. In all cases we found that the relative performance of the dynamic model did not change with the change in the parameter values. Below we present results for two such sensitivity analysis simulation experiments.

Since in a realistic setting the past tick's (t-1) gain is usually not available immediately, it has to be estimated and there can be noise in that estimate. We carried out simulation experiments to test the robustness of the dynamic model in the presence of noisy estimates. In the first set of simulation experiments we consider adding positive noise of 10% of the average gain to the value of last tick's gain that is used in any computation for the supplier selection. The actual gain values that are reported for performance results are not changed. In other words, the traditional model uses the noisy value of the gain from the past tick to decide whether to switch the supplier. For the dynamic and static models we use the noisy gain values in the FIG values computed using equation (23). In the second set of simulation experiments we add negative noise in the amount of 10% of the average gain.

Tables 2 and 3 show the results comparing the relative performance of the three supplier selection models on the buyers gain as well as the different suppliers' gain for the positive and negative noise, respectively. Although the individual gains of the buyer and suppliers change with the addition of the noise, the relative performance of both the static and dynamic models remains the same. This shows that the dynamic model is robust even in the presence of noise and not only provides the best gain for buyers and high quality suppliers but also is able to discriminate against and penalize low quality suppliers.

Supplier Selection Models		Buyer's Gain	Suppliers' Gain			
			Q0.8F 0.8	Q0.6F 0.6	Q0.4F 0.4	Q0.2F 0.2
Traditional	Avg	33.30	239.18	310.23	376.01	423.69
	Std/Avg	10.75	0.81	0.74	0.64	0.52
Static	Avg	261.30	385.76	315.94	244.00	175.40
	Std/Avg	1.41	0.74	0.73	0.70	0.76

	<i>Pw/Tr</i> <i>ad</i>	<b>1.94E-06</b>	<b>1.05E-07</b>	<b>n.s</b>	<b>1.30E-08</b>	<b>6.37E-10</b>
<b>Dynamic</b>	Avg	302.94	450.32	311.89	208.82	108.43
	Std/Avg	1.31	0.72	0.76	0.74	0.95
	<i>Pw/Tr</i> <i>ad</i>	<b>1.07E-07</b>	<b>7.93E-09</b>	<b>n.s</b>	<b>4.08E-09</b>	<b>6.45E-11</b>
	<i>Pw/St</i> <i>at</i>	<b>7.26E-03</b>	<b>1.96E-05</b>	<b>n.s</b>	<b>3.20E-03</b>	<b>1.36E-05</b>

**Table 2. Relative Performance of Different Supplier Selection Models for Positive Noise**

Supplier Selection Models		Suppliers' Gain				
		Buyer's Gain	Q0.8F 0.8	Q0.6F 0.6	Q0.4F 0.4	Q0.2F 0.2
<b>Traditional</b>	Avg	67.38	240.42	311.53	360.94	402.13
	Std/Avg	5.52	0.82	0.73	0.64	0.55
<b>Static</b>	Avg	247.62	390.26	320.78	254.18	169.57
	Std/Avg	1.57	0.73	0.73	0.72	0.77
	<i>Pw/Tr</i> <i>ad</i>	<b>2.93E-06</b>	<b>8.52E-08</b>	<b>n.s</b>	<b>6.28E-07</b>	<b>2.12E-10</b>
<b>Dynamic</b>	Avg	300.65	450.00	320.83	199.38	111.54
	Std/Avg	1.34	0.72	0.74	0.78	0.98
	<i>Pw/Tr</i> <i>ad</i>	<b>1.47E-06</b>	<b>2.41E-08</b>	<b>n.s</b>	<b>8.24E-09</b>	<b>8.88E-10</b>
	<i>Pw/St</i> <i>at</i>	<b>8.41E-03</b>	<b>4.04E-04</b>	<b>n.s</b>	<b>1.39E-04</b>	<b>1.32E-05</b>

**Table 3. Relative Performance of Different Supplier Selection Models for Negative Noise**

Fig. 5 summarizes the performance of the three models in terms of the distribution of the total gain among the buyers and suppliers across three different scenarios including the base scenario, one with positive noise and one with the negative noise. The dynamic model not only provides the best gain for the buyers, but also is the most robust in the presence of noise.

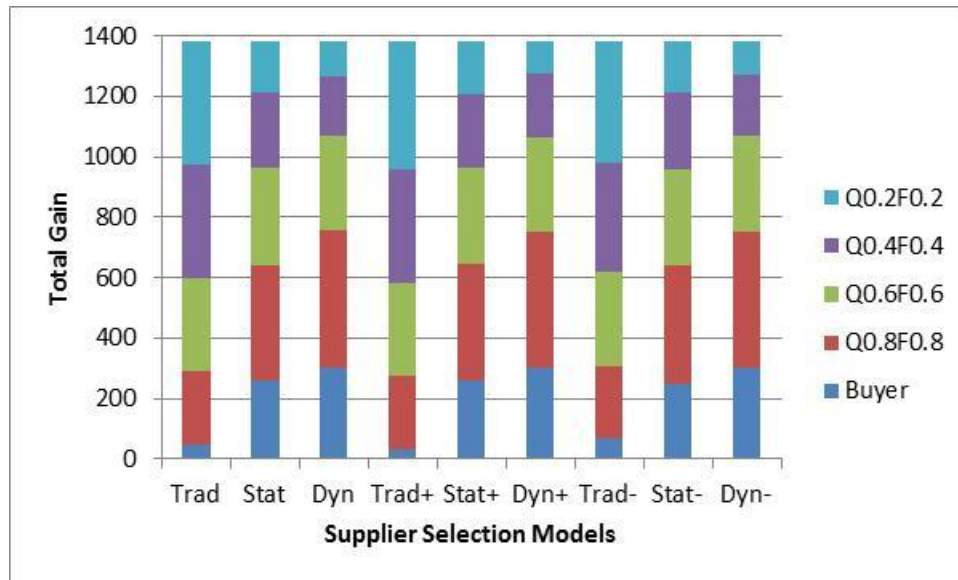


Figure 5. Distribution of total gain across models for different scenarios

## CONCLUSIONS

In the research, a dynamic supplier selection model is proposed, which provides a robust mechanism for selecting high quality and highly flexible suppliers that is not easily affected by noisy estimates of the actual gain from previous iterations. And a multi-agent simulation system was created to simulate the interactions among buyers and suppliers in an E-Procurement marketplace to test the proposed model. The performance of the proposed dynamic model was compared to that of other competing models. Results showed that the dynamic model outperformed other models in terms of rewarding buyers and desirable suppliers with better returns, in terms of identifying and discriminating against low quality and low flexible suppliers with less returns, and in terms of being robust in the presence of noise.

## LIMITATIONS

There are several limitations of the model proposed here. First, it requires a centralized system that functions both as the repository of the past transaction data for the buyers and suppliers and as the computation center to periodically calculate the all the needed FIG values. Although it is not uncommon for a number of major E-Procurement marketplaces to provide such a centralized system, our model undoubtedly demands tremendous computational resources based on the fact that

after each transaction the FIG values of each supplier has to be recalculated separately for each buyer. Our solution is to design and implement a more efficient distributed system for this model in the future. Finally, our study is limited to the investigation of how the use of a given supplier selection model influences the performance of the suppliers and buyers that are stick to one given strategy. However, one of the key purposes of the mechanism design is to change the agents' behavior for better and encourage their cooperation. Another limitation is that our experiment does not cover the cases of suppliers that are high quality and low performance or vice versa, since the preferred selection result would also relies on which factor is more important to the buyers. As all simulation related researches, due to the limit of resources, a study cannot exhaust all possibilities in reality, it can only test and investigate the most interesting scenario.

## FUTURE WORK

As mentioned in the limitations, we are to conduct more experiments to test other interesting scenario, such as situations with the presence of high-quality-and-low- performance suppliers plus the low-quality-and-high-performance suppliers to see if the proposed model still outperform other models. We consider studying the potential impact of different levels of noise on the performance of the proposed model. We also consider comparing the performance of the proposed model with other promising selection models in the E-Procurement marketplace. We are to take population ecology approach to see the evolution of the behavior of suppliers and buyers to determine which model works the best to lead to the cooperation among the suppliers and buyers. For instance, the suppliers could dynamically choose a strategy and switch from being high quality to low quality or vice versa, if it helps improve their gain, or the strategic suppliers could dynamically determine when and how to alter their flexibility. The buyers could also be designed more adaptive by allowing them to learn other parameters, for example, the temperature constant in Boltzmann distribution to improve their profit.

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