A Hybrid Agent-based Computational Economics and Optimization Approach for Supplier Selection Problem

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ABSTRACT
Supplier evaluation and selection problem is among the most important logistics decisions that have been addressed extensively in supply chain management. This logistics decision is also important in freight transportation since it identifies trade relationships between business establishments and determine commodity flows between production and consumption points. The commodity flows are then used as input to freight transportation models to determine freight movements and their characteristics including mode choice and shipment size. Various approaches have been proposed to explore this problem in previous studies. Traditionally, potential suppliers are evaluated and selected using only price/cost as the influential criteria and the state-of-practice methods. This paper introduces a hybrid agent-based computational economics and optimization approach for supplier selection. The proposed model combines agent-based multi-criteria supplier evaluation approach with a multi-objective optimization model to capture both behavioral and economical aspects of supplier selection process. The model uses a system of ordered response models to determine importance weights of different criteria in supplier evaluation from buyers’ point of view. The estimated weights are then used to calculate a utility for each potential supplier in the market and rank them. The calculated utilities enter a mathematical programming model in which best suppliers are selected by maximizing the total accrued utility by all buyers and minimizing total shipping costs while considering the supply capacity of supplier to ensure the market clearing mechanism. The proposed model is implemented in an operational agent-based supply chain and freight transportation model for the Chicago Metropolitan Area.

Keywords: supply chain management, supplier selection, agent-based computational economics, multiple criteria analysis, multi-objective optimization model
INTRODUCTION

Supplier evaluation and selection problems are among the most crucial logistics decisions that have been addressed extensively in supply chain management. For many business establishments, raw material purchases from outside suppliers account for a large percentage of their total operating costs. This logistics decision is also important from the freight transportation perspective since it can affect other logistics choices, related to supply chain and freight transportation, such as mode and shipment size choices. Result of supplier evaluation and selection decision identifies trade relationships between business establishments and determine commodity flows between production and consumption points in supply-demand market. These commodity flows are then used as input to freight transportation models to determine freight movements and their characteristics including mode choice and shipment size.

Various approaches have been proposed and used to explore the supplier selection problem in former studies. Traditionally, potential suppliers are evaluated using only price/cost as the influential criteria and the state-of-practice methods, such as standard optimization approaches are used to identify best suppliers and form optimum supply chains. However, review of literature revealed that selecting suppliers or vendors offering the lowest price is not “efficient sourcing” and does not necessarily result in the least total logistics cost (1, 2). In the modern supply chain management, multiple factors are taken into account when evaluating and selecting suppliers. Moreover, these traditional approaches cannot capture the complex behavioral interactions among decision makers in the markets and determine how buyers make discrete choices about from which suppliers to purchase. This has made the supplier selection problem more complicated than before.

Review of literature showed that numerous quantitative approaches incorporating multi-criteria have been proposed in former studies. Multi-objective optimization (MOP) (3, 4), analytic hierarchy process (AHP) (5, 6), data envelopment analysis (DEA) (7, 8, 9) and simple multi-attribute rating technique (SMART) (10, 11) are among the most common multi-criteria methods used to evaluate and select the best suppliers in a supply chain. All these methods have their advantages. However, most of these approaches are based on traditional theories in which the behavioral elements of supplier selection process are overlooked, and preferences and beliefs of decision-making agents are not captured.

This paper introduces a hybrid agent-based computational economics (ACE) and optimization approach for supplier selection problem. The proposed model combines an agent-based multi-criteria supplier evaluation approach with a multi-objective capacity constrained optimization model to capture both behavioral and economical aspects of supplier selection process for different markets. In the ACE approach, individual agents make supply chain decisions and interact with each other based on simple assumptions and rules in a simulated world. The described model in this paper is an ACE method that captures how buyer firms will make discrete choices about who to purchase from based on their preferences and in order to maximize their benefits while the model formulation ensures that supplier markets are optimal and Pareto efficient where each buyer cannot improve their condition without deteriorating other buyers’ condition.

The model uses a system of ordered response models to determine importance weights of different criteria such as cost, distance and reliability for evaluating suppliers from buyers’ point of view (12). Using the estimated importance weights and the value of measure under each criterion, for each potential supplier a utility value will be determined that presents the utility accrued by buyer if the potential supplier is selected. For each buyer then, the potential suppliers...
can be ranked based on the calculated. The estimated utilities enter a mathematical programming
model in which best suppliers are selected by maximizing the total accrued utility by all buyers
and minimizing total shipping costs. This ensures that the allocation of suppliers between buyers
is a Pareto Efficiency state in which it is impossible to make a buyer better off without making at
least another buyer worse off. Moreover, the model applies the market-clearing process by
considering the capacity of suppliers and demand of buyers as constraints, so that total demand of
buyers are met without exceeding the capacity of any suppliers or leftover of supplies.

In summary, the proposed study incorporates behavioral agent-based computational
economics mechanism in supplier evaluation and combine it with the standard constrained
optimization approach to develop a hybrid model that captures the behavioral aspects of decision-
making process in selecting suppliers by considering both buyers and suppliers characteristics, as
well as economical aspects of the supply-demand market by including logistics cost and
production capacity of suppliers in the structure of the optimization model. The proposed model
is implemented in an operational supply chains and freight transportation model for the Chicago
Metropolitan Area in which supply chains are simulated at highly disaggregated firm-level (13).

The rest of the paper is organized as follows. First, a brief review of existing studies on
supplier evaluation and selection problem is presented. The next section, explains the methodology
and model framework. It briefly discusses the system of ordered logit models described in (12)
and used to determine utility values associated with potential suppliers. Also, market clearing
algorithm and optimization model formulation is described. Moreover, in this section the datasets
that are used for model development and estimations are discussed. Finally, the model
implementation is described and some examples of model application are presented.

LITERATURE REVIEW
In a review work by Weber et al. (14), over 74 studies related to supplier selection criteria and
methods were reviewed and analyzed to classify the most important factors in supplier evaluation
while taking into account the significant changes in logistics and supply chain management
process. They argued that supplier selection process has changed considerably due to recent
revolutions in logistics and supply chain management methods such as improved computer
communications, technical advances and increased interest in just-in-time manufacturing
strategies. They also reviewed former studies that used quantitative and analytical methods to
select the most efficient suppliers for a supply chain. However, the focus of the study is on
identifying the most important criteria in supplier selection process.

De Boer et al. (15) presented a comprehensive review of decision methods supporting
supplier selection reported in academic literature. They proposed a step-wise framework for
supplier selection process including problem definition, formulation of criteria, evaluation of
potential suppliers and the final choice step. They discussed decision methods that can be used in
each step of the framework including a comprehensive exploration of the quantitative techniques
used in the last two steps of the framework, evaluation and final choice phases. The explored
decision methods for supplier evaluation (pre-qualification) include categorical methods, DEA,
cluster analysis (CA) and case-based-reasoning (CBR) systems and classified models of final-
choice phase include linear weighting models, total cost of ownership (TCO) models,
mathematical programming models, statistical models and artificial intelligence (AI)-based
models. All these quantitative models incorporate multiple criteria into their construction.
In another study, Ho et al. (16) extended and updated former literature reviews regarding supplier selection models including the study by De Boer et al. (15). They presented a comprehensive review of academic literature on multi-criteria decision-making (MCDM) models for supplier evaluation and selection. They classified all models applied in former studies into two main approaches; individual approaches and integrated approaches. Individual approaches include DEA, mathematical programming, AHP, case-based reasoning, analytic network process (ANP), fuzzy set theory, SMART and genetic algorithm (GA). Integrated approaches consists of integrated AHP and fuzzy models and some other integrated models applied in former studies.

They annotated former studies that applied any of modeling approaches in detail and identified the most prevalent evaluating criteria used in these studies. Finally, they explore possible inadequacy of existing approaches and further developments. Their review showed that AHP approach, with 17.95% share of all proposed models, is the most prevalent individual method in selecting supplier in a supply chain followed by mathematical programming models with 11.54% share. On the other hand, the integrated model of AHP and goal programming (GP) approach is the most frequently used integrated method. In addition, they found that price/cost is not the most widely used criterion in suppliers evaluating and selecting models. Instead, quality is the most frequently used factor followed by delivery. Cost/price takes the third place among the most prevalently used criteria in selecting suppliers.

In a recent study, Chai et al. (17) presented a literature review on studies that were published from 2008 to 2012 and explored decision models for supplier selection. They proposed a methodological decision analysis that contains four analytic aspects, including decision problems, decision makers, decision environments and decision approaches. In total, they reviewed 123 journal articles and classified them into seven groups based on their differences in uncertainties in supplier selection problem. They identified 26 decision-making techniques used in the reviewed studies and classified these techniques into three categories according to their problem solving perspectives, including multi-criteria decision-making techniques, mathematical programming techniques and artificial intelligence techniques.

They analyzed models in each class and explored the integration of different techniques for supplier selection model. Based on their review, MCDM techniques including AHP, ANP, SMART and techniques for order performance by similarity to ideal solution (TOPSIS) are the most prevalent approaches used for supplier selection problem in the reviewed articles. This is followed by mathematical programming techniques including DEA, linear and non-linear programming, multi-objective programming and GP and artificial intelligence techniques. They discussed proposed models in each category in former studies and provided recommendations for future research regarding the employment of MCDM techniques in supplier selection problem.

Recently, a new MCDM approach, called best-worst multi-criteria decision-making method (BWM), has been developed by Rezaei (18) to solve MCDM problems such as supplier selection. Based on the study by Rezaei (18), the BWM method outperforms the existing MCDM approaches. It requires less comparison data and leading to more consistent comparisons and more reliable results.

**METHODOLOGY AND MODEL FRAMEWORK**

This section describes the hybrid agent-based computational economics and optimization approach used to determine supply chains between business establishments. First, the agent-based supplier
evaluation and the data used for development of the model are described. Then the constrained optimization supplier selection model and the major input data sources are explained. Interested readers can find more detailed information about the model development process and utilized data in (12) and (13).

Agent-based Multi-criteria Supplier Evaluation Model
As described above, the first step of the supplier selection approach is an agent-based multi-criteria supplier evaluation model. This model determines a utility value for all potential suppliers of each buyer and rank them based on the calculated value. The estimation of utility is based on important characteristic of both buyer and supplier (such as industry type, employee size and location) and a set of importance rates. The importance rates present importance weight of different criteria (such as cost, reliability and delivery) for buyer in selecting a supplier. Therefore, the model tries to replicate behavior of buyers in evaluating potential suppliers in the real market.

Data
To estimate the proposed behavioral agent-based supplier evaluation model, a comprehensive and detailed dataset on the characteristics of decision-makers and other logistics components of supply chain is required. To understand how individual buyers rank different criteria in evaluating potential suppliers and what are the influential characteristics of these decision-makers, an online establishment survey has been carried out in three waves at the University of Illinois at Chicago (UIC) (19). The study aimed for shipping managers of firms or someone with acceptable knowledge about logistics choices of the firm as the survey participants.

The survey explored the discrete choice of supplier selection and investigated influential factors in this logistics choice. A key goal of the survey was shed light on the decision-making process of supplier selection and determine the most important criteria affecting the choice of suppliers in a supply chain. A list of eight important criteria has been included in the survey using results of an extensive literature review and respondents were asked to rank every criterion on a scale from one to five where one represented low importance; three, medium; and five, high. Therefore, instead of simply asserting which characteristic was more valued, respondents had the ability to demonstrate how much more valued a characteristic is. The examined criteria include cost, credit and finance, delivery, distance and convenience, loyalty, management and service, manufacturing capacity and reliability, and quality and technology which cover a wide range of important factors in evaluating suppliers.

The last wave of the survey that explored the logistics choice of supplier selection resulted in 570 completed surveys which were used in this study. Respondents from a diverse range of industry types participated in this wave of survey. A majority of respondents categorized their industry as manufacturing followed by Wholesale Trade and Retail Trade. Thus, various commodity types are covered in the survey. The survey also covered respondents with a broad geographic distribution. Respondents from 48 states and District of Columbia participated in the survey. New Hampshire and Wyoming were the only two unrepresented states, though potential respondents in both states were targeted in the survey. Illinois was by far the most represented state, followed by Ohio and California. Also, detailed information about the establishments and their logistics decisions are obtained from the survey that makes the dataset a unique source of information to develop logistics choice models.
As shown in FIGURE 1 below, the results depict a significantly different picture of how suppliers are chosen. All characteristics have been assigned values that average above the “medium,” indicating that none are generally considered low importance. Quality and technology, delivery, manufacturing capacity, and cost, which refers to the purchase fee or price of commodity, are given high values with the average value of higher than four, though cost is ranked lower than the other three factors.

The obtained data on the importance rating of the criteria and detailed information about the characteristics of decision-maker firm (buyer) provided valuable information for development of a system ordered-response models that can estimate importance rates of these criteria for each decision making firm when evaluating its potential suppliers.

**Importance Rates Modeling Approach**

Providing ratings are among common questions asked from participant in surveys. The question, asked in the UIC survey about importance rating of each criterion in supplier selection, is an example these questions. As it is discussed by Train (20) the key characteristic of rating questions, from a modeling point of view, is that the potential responses are ordered. Thus, due to the ordered nature of alternatives, a dependency pattern exists among them. In other words, there is more similarity between closer alternatives and more dissimilarity between alternatives that are further away. Therefore, the logit model’s assumption of independent error terms for individual alternative does not apply and a standard logit specification is not compatible with the ordered nature in this case. Therefore, the ordered logit structure which uses the logistic distribution on ordered alternatives model and was employed to determine importance rates of criteria.

Many observed and unobserved factors affect decision maker’s (respondent’s) opinion on the importance of different criteria in supplier selection problem. Observed factors include...
characteristics of decision maker (buyer) including employee size, industry type, number and amount of inbound shipments, and other logistics choices of supply chain. Assume that $U$ represents buyer’s level of utility associated with importance rate of questioned criterion. Assuming that this random utility level includes observed and unobserved components, it can be written as follows.

$$U = \beta'X + \varepsilon$$ (1)

where $\beta$ is a vector of coefficients that corresponds to the vector of independent variables $X$ (observed factors) and $\varepsilon$ represents the unobserved factors (error terms) which are considered random. Distribution of error terms determines the probability for the five potential responses.

To obtain the propensity of choosing a potential rank, only the distribution of $\varepsilon$ is needed. In this study, it is assumed that error terms are distributed logistics with a cumulative distribution function given by $F(.)$ which is defined as follows.

$$F(\varepsilon) = \frac{e^\varepsilon}{1+e^\varepsilon}$$ (2)

The probabilities enter the log-likelihood function and parameters in the model are estimated by maximizing the log-likelihood using an econometrics software. The parameters to be estimated include coefficient vectors $\beta$, which presents the effect of explanatory variables on decision-makers’ opinion of importance rates and the cutoff levels $(k_1, ..., k_4)$ for the potential ordinal responses associated with the five level of rating scale.

For each of eight criteria presented in FIGURE 1, an ordered logit model is developed using SAS econometrics software. For each model, the Score Test for the Proportional Odds Assumption is performed which is the Chi-Square Score Test for the Proportional Odds Assumption. The models’ fit is assessed by the Akaike information criterion (AIC) and Schwarz Criterion (SC) which are based on the likelihood function at convergence. The model with the smallest AIC and SC is considered to have the best fit and selected as the preferred model. In addition, the global null hypothesis is tested using three asymptotically equivalent Chi-Square tests including Likelihood Ratio and Wald test. TABLE 1 presents results of model estimation for all criteria, number of observations and tests results. Exogenous variables that are considered in the models estimation are mainly decision-makers’ (i.e., buyers) characteristics, including industry type, production/consumption rates, and number of employees. P-values for estimated coefficients of predictors are presented in parentheses in the table. More detailed information about the model estimation results can be found in (12).
### TABLE 1 Ordered Logit Model Estimate for Importance Rating of Supplier Evaluation Criteria (values in parentheses are P-values)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Criterion</th>
<th>Cost</th>
<th>Credit/Financial Status</th>
<th>Delivery</th>
<th>Distance/Convenience</th>
<th>Loyalty</th>
<th>Management/Service</th>
<th>Capacity/Reliability</th>
<th>Quality/Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model Constant</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Intercept 1</td>
<td></td>
<td>-0.3039</td>
<td>(0.17)</td>
<td>-1.6509</td>
<td>0.4454</td>
<td>-2.0280</td>
<td>-0.9023</td>
<td>-1.8005</td>
<td>-0.4290</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.8297</td>
<td>(0.00)</td>
<td>-0.2977</td>
<td>1.9999</td>
<td>-0.8842</td>
<td>0.5495</td>
<td>-0.0851</td>
<td>1.1621</td>
</tr>
<tr>
<td>Intercept 2</td>
<td></td>
<td>2.6240</td>
<td>(0.00)</td>
<td>1.5475</td>
<td>3.8827</td>
<td>0.5300</td>
<td>2.1817</td>
<td>1.5957</td>
<td>2.7760</td>
</tr>
<tr>
<td>Intercept 3</td>
<td></td>
<td>3.6627</td>
<td>(0.00)</td>
<td>2.5639</td>
<td>4.3449</td>
<td>1.5138</td>
<td>3.5671</td>
<td>3.5179</td>
<td>4.0389</td>
</tr>
<tr>
<td>Intercept 4</td>
<td></td>
<td></td>
<td></td>
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<td><strong>Industry type</strong></td>
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</tr>
<tr>
<td>Agriculture, Forestry, Fishing</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-1.5721</td>
<td>-1.0328</td>
<td></td>
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<td>Hunting (NAICS 11)</td>
<td>(NAICS 23)</td>
<td>1.7117</td>
<td>(0.11)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-1.7381</td>
<td>-0.8759</td>
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</tr>
<tr>
<td>Manufacturing (NAICS 31-33)</td>
<td></td>
<td>0.3604</td>
<td>(0.06)</td>
<td>0.3079</td>
<td>-</td>
<td>-0.3404</td>
<td>0.7795</td>
<td>-</td>
<td>0.3502</td>
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<tr>
<td>Wholesale Trade (NAICS 42)</td>
<td></td>
<td>-</td>
<td>(0.26)</td>
<td>-</td>
<td>0.3697</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
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<tr>
<td>Retail Trade (NAICS 44-45)</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.4192</td>
<td>0.5675</td>
<td></td>
</tr>
<tr>
<td>Transportation and Warehousing</td>
<td></td>
<td>-</td>
<td>(0.13)</td>
<td>-0.6466</td>
<td>0.6466</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.6467</td>
</tr>
<tr>
<td>(NAICS 48-49)</td>
<td>(NAICS 51)</td>
<td>-</td>
<td>-</td>
<td>1.0559</td>
<td>(0.13)</td>
<td>-</td>
<td>1.7459</td>
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<td>2.2909</td>
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<td><strong>Production/Consumption</strong></td>
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<tr>
<td># of Weekly Inbound Shipments</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.0002</td>
<td>-</td>
<td>-</td>
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<tr>
<td># of Weekly Outbound Shipments</td>
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<td>-</td>
<td>-</td>
<td>-0.00348</td>
<td>(0.03)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.000318</td>
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<td>-</td>
<td>(0.24)</td>
<td>-901E-12</td>
<td>(0.24)</td>
<td>-</td>
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<tr>
<td>Average annual value of outbound</td>
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<td>-</td>
<td>(0.19)</td>
<td>0.5157</td>
<td>(0.05)</td>
<td>-</td>
<td>0.8426</td>
<td>0.5155</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>0.8426</td>
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<tr>
<td>Truck</td>
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<td>-</td>
<td>-</td>
<td>0.2889</td>
<td>(0.19)</td>
<td>-</td>
<td>0.3908</td>
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<tr>
<td>Air</td>
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<td>-</td>
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<td>Marine</td>
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<td>Mail/Courier</td>
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<td>-</td>
<td>0.2171</td>
<td>(0.19)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Variables</td>
<td>Criterion</td>
<td>Cost</td>
<td>Credit/Financial Status</td>
<td>Delivery</td>
<td>Distance/Convenience</td>
<td>Loyalty</td>
<td>Management/Service</td>
<td>Capacity/Reliability</td>
<td>Quality/Technology</td>
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<td>----------------------------------------</td>
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<tr>
<td><strong>Number of Employee</strong></td>
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<tr>
<td>1-50</td>
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<td>-0.2877</td>
<td>-0.7581 (0.00)</td>
<td>-0.3842</td>
<td>-0.2919 (0.013)</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>&gt;250</td>
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<td>-</td>
<td>-</td>
<td>-0.3367</td>
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<tr>
<td><strong>Other Characteristics</strong></td>
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<td></td>
<td></td>
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<tr>
<td>Floor Area of the establishment (sq. ft.)</td>
<td>4.506E-7</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-2.78E-7 (0.03)</td>
<td>-3.34E-7</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>#of light trucks owned by the company</td>
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<td>-0.00478</td>
<td>-0.00478 (0.09)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
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<tr>
<td># Observations</td>
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<td>427</td>
<td>503</td>
<td>410</td>
<td>519</td>
<td>468</td>
<td>475</td>
<td>455</td>
<td>508</td>
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<td>-720.0</td>
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<td>-797.7</td>
<td>-630.7</td>
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<td>Chi-square</td>
<td></td>
<td>21.7452</td>
<td>27.9665</td>
<td>165.1382</td>
<td>31.9904</td>
<td>10.1371</td>
<td>31.0478</td>
<td>163.9856</td>
<td>8.0359</td>
</tr>
<tr>
<td>SC</td>
<td></td>
<td>1117.787</td>
<td>1495.898</td>
<td>910.508</td>
<td>1657.865</td>
<td>1316.678</td>
<td>1282.297</td>
<td>1031.045</td>
<td>1100.070</td>
</tr>
</tbody>
</table>
Supplier’s Utility

Once that model parameters are estimated, the model can be used to evaluate each supplier by converting multiple measures under all criteria into a single utility value using the obtained probabilities of importance rating of all criteria. Assume that buyer \( n \) has a subset of \( I_n \) \((i = 1, 2, 3, \ldots, I)\) as potential suppliers. Let \( r_{nj} \) be the estimated importance rate of evaluation criterion \( j \) \((j = 1, 2, \ldots, 8)\) for buyer \( n \). Using simple transformation formula in the equation (3), importance rate \( r_{nj} \), can be transformed to \( w_{nj} \), the normalized weight of criterion \( j \) for decision maker \( n \).

\[
 w_{nj} = \frac{r_{nj}}{\sum_{j=1}^{8} r_{nj}} 
\]

(3)

Assume that \( x_{ij} \) presents the measure for supplier \( i \) under criterion \( j \) which can be either positively (such as reliability) or negatively (such as cost or distance) related to the utility of supplier \( i \). For the criteria that are negatively related to the utility of supplier, \( x_{ij} \) represents the inverse value of the measure. All measures of supplier \( i \) under all criteria \((x_{ij} \ (\forall \ j; \ j = 1, 2, \ldots, 8))\) are assumed to be normalized into a common 0-1 scale using a linear transformation method. Therefore, no criterion takes domination over others due to the large scale of measure. The utility of potential supplier \( i \) for buyer \( n \), under all criteria, can be obtained as \( U_{ni} \).

\[
 U_{ni} = \sum_{j=1}^{8} w_{nj} x_{ij} 
\]

(4)

It should be noted that some of the measures that are challenging to quantify, can be proxied using a correlated measure. For example, “credit/financial status” of suppliers is proxied with their “total sales value” or “total production value”.

Market-Clearing: Constrained Optimization Model

For each buyer, agent-based supplier evaluation model can be used to calculate utility of its potential suppliers and prioritize them based on the estimated utility. The next step in the model framework is to select the best suppliers to cover buyers’ demand. A market-clearing approach is applied to select the best suppliers from the potential set of suppliers in a way that the supply (traded commodity) is equated to the demand. Market-clearing is the mechanism of allocating resources from selected suppliers to the set of buyers in market. As discussed in the literature review, different methods can be applied for maker-clearing and selecting suppliers. The selected method should be optimal and stable to ensure market-based economic efficiency and replicate the real-world market’s conduct (commodity flow).

The proposed market-clearing method is a constrained optimization which is an optimal and stable mechanism that establishes economic efficiency and ensures that there is no leftover supply or demand. The proposed model uses a number of objective functions that need to be maximized or minimized subject to a number of conditions that adjust functions’ solution space and ensure primary goals of the study. Specifically, the model takes the estimated utility of potential suppliers from step one as input and maximizes the total accrued utility of selected suppliers. Moreover, it minimizes total shipping cost of moving commodities from suppliers to buyers which is a key logistics component in supplier selection and supply chain formation. It also ensures that the total demand of buyers is covered while considering the capacity of suppliers (available supply).

Data
Several datasets is required for the estimation and implementation of the optimization model. The main input data is the suppliers’ utility values obtained from ordered response model. Other input datasets include the shipping cost matrix between each supplier and buyer, available supply and demand of supplier and buyer firms for each commodity market, three dimensional crosswalks for identifying industry industry-to-industry trade patterns for each commodity market that are developed in another study (13).

**Model Structure**

The proposed constrained optimization model is defined as follows. The model has a multi-objective linear structure.

Maximize \( z_1 = \sum_{n\in N} \sum_{i\in Q_n} U_{ni} y_{ni} \)  

(5)

Minimize \( z_2 = \sum_{n\in N} \sum_{i\in Q_n} C_{ni} d_n y_{ni} \)  

(6)

Minimize \( z_3 = M \)  

(7)

Subject to

\[ \sum_{n\in N} d_n y_{ni} - S_i \leq M \quad (\forall \ i \in Q_n) \]  

(8)

\[ \sum_{i\in Q_n} y_{ni} = 1 \quad (\forall \ n \in N) \]  

(9)

\[ 0 \leq y_{ni} \leq 1 \quad (\forall \ n \in N, \forall \ i \in Q_n) \]  

(10)

where the variables used in the model are defined as follows.

- \( N \): set of all buyers looking for best suppliers to cover their demand
- \( Q_n \): the set of potential suppliers for the buyer \( n \)
- \( U_{ni} \): Utility of supplier \( i \) under all criteria for decision maker \( n \) calculated from equation (4)
- \( y_{ni} \): coverage fraction, the fraction of demand of the buyer \( n \) that is covered by supplier \( i \)
- \( C_{ni} \): total transportation cost of a unit of shipment from supplier \( i \) to buyer \( n \)
- \( d_n \): total of demand of buyer \( n \)
- \( S_i \): total supply capacity of supplier \( i \)
- \( M \): a dummy variable, used to transfer \( z_3 \) to linear form, defined by the following equation

\[ M = \text{Maximize} (\sum_{n\in N} d_n y_{ni} - P_i) \]  

(11)

Using above definitions, objective function \( z_1 \) maximizes total accrued utility from selecting best suppliers. Objective function \( z_2 \) minimizes total shipping costs of total commodity flows. The objective function \( z_3 \) originally has the following non-linear form.

\[ z_3 = \text{MinMax}(\sum_{n\in N} d_n y_{ni} - P_i) \]  

(12)

However, as stated earlier, the dummy variable \( M \) along with constraint (8) are used to transform \( z_3 \) to linear form. This objective function along with constraint (9) ensures that there is no leftover of supply and demand. It makes sure that none of suppliers is overloaded with demands more than its supply capacity and tries to allocate demand between suppliers in a way to that all their available supply is used. Constrain (9) indicates that total demand for each buyer have to be covered by its selected suppliers and constraint (10) depicts \( y_{ni} \)'s as the fraction of demand that will be covered by a supplier.
**Solution Method**

To solve the multi-objective model, different approaches can be used including the scalarization technique, ε-constraints method, goal programming (GP) and multi-level programming. One of the hybrid approaches that has been recently in the research focus is the fuzzy goal programming (FGP). FGP is obtained by applying fuzzy set theory in goal programming. In GP, for each objective function, specific value or bound (goal) is defined and model tries to minimize sum of deviations from defined goals. GP is an extension form of linear programming (LP) and in the case that LP is infeasible, GP can provide a close answer to the defined goals. It is very difficult especially in real world to determine the goals for objective functions. So to deal with this fuzziness and imprecision, FGP applies fuzzy set theory to GP by assigning a fuzzy membership function to each objective function. The first FGP method was introduced by Narasimhan (21) and one year later Hannan (22) proposed equivalent LP of Narasimhan’s method. Several studies used FGP method to solve multi-objective optimization problem (23). The FGP method is also used to solve the proposed optimization problem in the current study.

Using this method, the supplier selection allocations between suppliers and buyers will be *Pareto Efficient* where each buyer cannot be made better off without making other buyers worse off. This results in a stable and optimal market. However, it should be noted that the selected set of suppliers can change by using a different market clearing method (e.g. auction method instead of mathematical programming) or by changing the priority of objective functions in the FGP approach.

**MODEL APPLICATION AND RESULTS**

The proposed supplier selection model is implemented in an agent-based supply chain and freight transportation model for Chicago Metropolitan Area to replicate supplier selection process at the individual firm level and form firm-to-firm supply chains. The Chicago agent-based supply chain model uses disaggregate behavioral based logistics and transportation choice models to simulate commodity flows at highly disaggregate firm level (13). FIGURE 2 presents the modular structure of the Chicago model. The agent-based freight transportation model has as a three-layered framework. In the first layer, “Economic Activity”, the agents (firms) in the study area are generated and their characteristics are determined. Several economic factors, a considerable set of data sources and a complex procedure is used to determine input and output values of different commodity types for these firms. The second layer is the “Logistics Decisions” in which the logistics components of supply chains are determined in a step-wise process. First, in this layer the trade relationships between firms are formed and supplier-buyer pairs are identified using the proposed hybrid supplier selection model in this paper. Total annual commodity flows between firms are determined using the results of supplier selection model. Next, the logistics choices including shipment size, transport mode and shipping chain choice are determined firm-to-firm commodity flows. The final layer, “Network Analysis”, deals with the assignment of commodity flows to the transportation networks which allows further analysis and model validation.

As the Figure shows, supplier selection processes are simulated within the logistics decision layer. Results of this step identifies trade relationships between business establishments and determines commodity flows between supplier and buyer firms in 14 different markets. The estimated commodity flows are then used as inputs in other steps of the logistics model to
determine disaggregate freight flows and their characteristics including mode, shipment size and usage of intermediate handling facility.

FIGURE 2 The agent-based supply chains and freight transportation model framework for Chicago
TABLE 2 presents the total estimated commodity flows for different markets (classes of commodities) and compares them with the Freight Analysis Framework (FAF) commodity flows. It should be noted that the estimated firm-level flows are aggregated to the FAF zone level, so they can be compared with FAF flows.

As the table shows, the supplier selection model simulates 85.1% (around 12 billion tons) of 2007 FAF domestic commodity flows that are transported by truck, rail, air and courier modes. This difference between total commodity flows can be due to the exclusion of very small supplier and buyer firms from this study in order to reduce the computational complexity of optimization model. These small firms generate very small commodity flows that are ignored in this study. As the table shows, although the maximum value of estimated flows are much smaller than maximum flow in FAF data, the average value of estimated flows is much bigger than the FAF data. Considering the huge intervals between minimum and maximum values of FAF commodity flows, it can be concluded that the distribution of flows in FAF data is skewed toward smaller commodity flows while the proposed model simulates more homogenously distributed commodity flows.

FIGURE 3 shows the replicated commodity flows for “Electronics, Electrical and Precision Equipment” market as an instance of the output of Supplier Selection Model for the Illinois state. It compares the estimated commodity flows with FAF commodity flow patterns. It should be noted that the firm-level commodity flows are aggregated to the zone level flows for this presentation.

<table>
<thead>
<tr>
<th>Commodity Class (market)</th>
<th>FAF Flows (KTON)</th>
<th>Estimated Flows (KTON)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>Min</td>
</tr>
<tr>
<td>Agriculture and Forestry Products</td>
<td>2,842,869</td>
<td>0.001</td>
</tr>
<tr>
<td>Products of Mining</td>
<td>4,371,775</td>
<td>0.001</td>
</tr>
<tr>
<td>Petroleum Products</td>
<td>1,448,457</td>
<td>0.001</td>
</tr>
<tr>
<td>Chemical and Pharmaceutical Products</td>
<td>668,304</td>
<td>0.001</td>
</tr>
<tr>
<td>Wood Products</td>
<td>875,363</td>
<td>0.001</td>
</tr>
<tr>
<td>Paper Products</td>
<td>265,028</td>
<td>0.001</td>
</tr>
<tr>
<td>Nonmetallic mineral products</td>
<td>1,316,807</td>
<td>0.001</td>
</tr>
<tr>
<td>Metal and Machinery Products</td>
<td>679,572</td>
<td>0.001</td>
</tr>
<tr>
<td>Electronic, Electrical &amp; Precision Equipment</td>
<td>60,107</td>
<td>0.001</td>
</tr>
<tr>
<td>Motorized &amp; Transportation Vehicles &amp; Equipment</td>
<td>141,682</td>
<td>0.001</td>
</tr>
<tr>
<td>Household and Office Furniture</td>
<td>35,406</td>
<td>0.001</td>
</tr>
<tr>
<td>Plastic, Rubber and Miscellaneous Manufactured Products</td>
<td>274,305</td>
<td>0.001</td>
</tr>
<tr>
<td>Textiles and Leather Products</td>
<td>51,625</td>
<td>0.001</td>
</tr>
<tr>
<td>Waste and scrap</td>
<td>1,276,473</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>14,307,773</strong></td>
<td><strong>0.001</strong></td>
</tr>
</tbody>
</table>
FIGURE 3 Simulated and FAF flows for “Electronic, Electrical, and Precision Equipment” market, Illinois.
(a) Simulated flows. (b) FAF flows.
As the figure shows, the simulated flows are different from the FAF commodity flow patterns. Although the commodity flow ranges are similar, the distribution of flows within this range is completely different. While there are more small size (KTON) flows presented in FAF data, the estimated commodity flows in this paper are more evenly distributed by size (KTON). This difference can be due to the exclusion of small production and consumption values from this study. These small production and consumption values generate small size commodity flows. However, since they are excluded from this study, small size commodity flows are underestimated. Also, this study uses a behavioral optimization supplier selection model to simulate commodity flows while the FAF model employs a data mining-based flow matrix construction technique to estimate commodity flows. The differences between the approaches used for estimation of commodity flows in the two studies can be another source of dissimilarities between FAF and simulated commodity flows. In order to more clearly show the differences between FAF estimates and simulated flows for this commodity, distribution of flows by size are presented in Figure 4. The same analysis was performed for other 13 markets which resulted in similar outcome and conclusion.

**FIGURE 4** Simulated and FAF flows for “Electronic, Electrical, and Precision Equipment” market, Illinois.

**CONCLUSION**
Supplier selection is of great interest in logistics and supply chain management. Different models have been proposed to study the supplier evaluation and selection problem including DEA, AHP and mathematical programming method. The current study proposes an innovative hybrid agent-based model that integrates agent-based computational economics with constrained optimization approach to select best suppliers for individual buyer firms and determine commodity flows at
firm-to-firm level. The advantage of using this hybrid supplier selection approach is that the first
step considers the behavioral aspects of the problem by including the characteristics of decision-
makers in the modeling structure and capturing their effects on evaluating suppliers and
determining their associated utility. The second step takes into account the decision makers’
opinion on suppliers’ utility and includes transportation costs to select the best suppliers using a
constrained optimization model. The proposed hybrid approach is a behavior-based optimal and
stable model that ensures economic efficiency of studied markets. Therefore, it tries to replicate
the real-world commodity flows.

As with any agent-based computational economics models, the data must be sufficient
and comprehensive in order to ensure that markets clear. Therefore, a freight establishment
survey was conducted to acquire the data. A key component of the survey questionnaire design
was to understand the decision-making process of supplier selection and identifying the most
important criteria affecting the choice of suppliers in supply chains. Thus, the obtained data
could be used to develop a more precise and disaggregate supplier selection model.

The proposed model was implemented in an agent-based freight transportation model to
simulate the supplier selection processes along with other logistics choices for individual
business establishments. The results of the model application showed that the model performs
well and achieves the main goals of the study. There were some differences between the
aggregated simulated supply chains and observed commodity flow pattern in FAF data. These
differences can be explained to some extent. However, more detailed data is required to further
calibrate and validate the model.
REFERENCES


