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A hybrid ensemble and AHP approach for resilient supplier selection

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Abstract Suppliers play a crucial role in achieving the supply chain goals. In the context of risk management, suppliers are the most common source of external risks in modern supply chains. The recognition that continuity of supply chain flow under disruptive event is a critical issue has brought the attention of companies to the selection of resilient suppliers. In contrast to the extensive number of researches on traditional and green criteria of supplier selection, the criteria associated with resilient supplier selection are not well explored yet. This paper first seeks to explore the resilience criteria for supplier selection based on the notion of resilience capacities which can be divided into three categories: absorptive capacity, adaptive capacity, and restorative capacity. Absorptive capacity refers to the capability of system to withstand against disruptive event in prior or called as preparedness of supplier, while adaptive and restoration capacities imply the capability of supplier to adopt itself and restore from disruption or recoverability of supplier. We identified eight effective elements for resilience capacities which contribute to the resilience of suppliers. Advanced data mining approaches like predictive analytics models are used to predict the resilience value of each supplier. We applied ensemble methods by combining binomial logistics regression, classification and regression trees, and neural network to obtain better predictive performance than individual algorithm from the historical data to predict individual supplier's resiliency. This resilience value, obtained from ensemble methods, is coupled with additional four variables to assess the suppliers' overall performance and rank them using different supplier selection models. Finally, a case study has been performed on international plastic raw material suppliers for a U.S. based manufacturer.

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Introduction

Supply chain management is becoming increasingly significant to achieve competitiveness in the current business environment as the paradigm for corporate management has been rapidly shifted from competition between individual firms to the competition between supply chains in recent years (Cho et al. 2008). In supply chain management, the relationship between supplier and buyer has significant impact on the success of meeting strategic goals of a company. Hence it is necessary for a buyer to keep track of their relationship and evaluate supplier's performance, and optimize its supply base.

Manufacturing companies need to collaborate with various suppliers to continue their business activities. In manufacturing industries, the raw materials and component parts can amount up to 70 % of the finished product cost. The procurement department has significant influence on cost reduction, and supplier selection is the most critical function of this department (Stueland 2004). Supplier selection and assessment is the process of finding capable supplier who is able to supply high quality products on right time at the right price. Supplier selection is a multi-criteria decision making problem that involves two major tasks. One is to determine criteria to be considered, and the another one is the methods to compare the eligibility of suppliers. In general, the traditional supplier selection criteria can be divided into two categories: qualitative and quantitative. Different qualitative criteria of suppliers such as transportation, purchasing and order costs, delivery time, product defect rate, and qualitative criteria such as product quality, warranties and claim policies, performance history, technical capability, geographical location, desire of business, and labor relations record are considered in the previous studies (Liao and Kao 2011; Ozkok and Tiryaki 2011; Arikan 2013; Toloo and Nalchigar 2011; Du et al. 2015; Al Khaled and Hosseini 2015; Guneri et al. 2011; Abdollahi et al. 2015; Karsak and Dursun 2014; Kilincci and Onal 2011; You et al. 2015; Kumar Kar 2014). Green supplier selection criteria have received a great deal of attentions from both academics and practitioners due to environmental standards and regulations imposed by governments to companies. Green supplier selection is developed with intent of focusing on meeting government regulations, process improvement, and buying company's environmental policy (Humphreys 2003). Humphreys (2003) categorized the green supplier criteria into two classes: quantitative and qualitative environmental criteria. Quantitative environmental criteria include environmental regulations that can be measured quantitatively such as pollutant cost and improvement cost, while qualitative environmental criteria focuses on qualitative measurements associated with environmental capability of supplier such as green image, environment management systems, environment competencies, etc. Interested readers about green supplier selection are referred to Hosseini and Al Khaled (2014), Buyukozkan and Cifci (2012), Chiou et al. (2008), Grisi et al. (2010), Hong-jun and Bin (2010), Hsu et al. (2013), and Igarashi et al. (2013). Depending on the context of supplier selection problem in terms of specific industry and specific characteristics of products, goods, and services, several authors have classified supplier selection criteria as summarized in Table 1. From Table 1, it is obvious that previous researchers mainly focused on traditional and green supplier selection criteria.

Although many research efforts have been made to the supplier selection based on traditional and green criteria, resilient criteria have not been well explored yet. The notion of resilience has become very important in the scope of supply chain management. Supplier disruptions can impose huge loss to the entire supply chain by discontinuing supply flows. For instance, a devastating earthquake measuring 7.3 on the Richter scale hit central Taiwan on 21 September 1999, which was the largest earthquake in the area in almost 65 years, killed 2300, injured 8000 people, and destroyed 100,000 homes (Chen et al. 2007). The impact of disaster has severe consequences for many manufacturing industries, organizations, infrastructures, where the total industrial production losses were approximated about $1.2 billion (Papadakis 2006). The Hsinchu Industrial Park lay within 70 miles of earthquake epicenter, which includes many large scale semiconductor fabrication facilities that are estimated to account for roughly 10 % of the world's production of computer memory chips (Bhamra et al. 2011). The impact of earthquake disaster on PC supply chain was dramatic. Supply of PC's components was constrained during the following months due to the intensity of damages caused by earthquake disaster. Companies such as Dell, Gateway, IBM, Apple, HP were all adversely affected by the supplier disruption. In 2011, an earthquake of magnitude 9.0 and tsunami hit in Japan, resulted in disrupting global supply chain networks (Manual 2013). The aforementioned examples indicate that the supply chain flow must continue even under devastating disasters. To ensure continuity of supply flow, resilient supplier selection criteria must be taken into account. Singh (2014)

Table 1 Classification of supplier selection criteria

References	Criteria
Chan et al. (2007)	Performance, continuous improvement, company background
Huang and Keskar (2007)	Product, supplier, society
Sen et al. (2008)	Cost, quality, service, reliability, management, technology
Luo et al. (2009)	Management, financial quality, company resource and quality
Sen et al. (2009)	Socio-economic, technology, quality
Kahraman and Kaya (2010)	Supplier, product performance, service performance, cost
Rezaei and Ortt (2013)	Element of exchange, supplier, relationship
Kumar Kar (2014)	Price, delivery compliance, product, technological capability, production capability, financial position, E-transaction capability
Guneri et al. (2011)	Quality, cost, on-time delivery, relationship closeness, conflict resolution
Arikan (2013)	Price, quality, delivery, capacity
Deng et al. (2014)	Cost, quality, service performance, supplier's profit, risk factor
Our paper	Resilience (surplus inventory, location separation, backup supplier contracting, robustness, reliability, rerouting, reorganization, restoration), cost, quality, lead time, response time

presents a hybrid algorithm that prioritizes the suppliers and then allocates the demand among the suppliers. Choudhary and Shankar (2013) proposed a mathematical model for joint decision of procurement lot-size, supplier selection and carrier selection. Other works related to supplier selection can be found in (Masi et al. 2013; Luo et al. 2009; Lienland et al. 2013).

In this paper we identify the resilient criteria for supplier selection based on supplier's resilience capacity. Supplier's resilience capacity involves three related components: absorptive, adaptive, and restorative capacities, explained in details in "Contributors to resilient supplier" section.

The rest of this paper is organized as follows: : "Contributors to resilient supplier" section identifies and highlights contributors to the resilient supplier selection. "Literature to supplier selection" section reviews proposed hybrid approach for solving resilient supplier selection problem. Simulation results for case study are given in "Resilience Prediction Model" section, and finally the paper ends with conclusion in "Analytic hierarchy process (AHP)" section.

Contributors to resilient supplier

Resilience has been defined by various researchers and institutes; however, there is no consensus on definition of resilience. Sheffi (2006) defined the resilience as "the company's ability to, and speed at which they can, return to their normal performance level (e.g., inventory, capacity, service rate) following by disruptive event". American Society of Mechanical Engineers (2009) defined resilience as the ability of a system to sustain external and internal disruptions without discontinuity of performing the system's function or fully to recover if the system's function is disconnected. Pettit et al. (2011) stated that the resilience capability facilitates a supply chain to return its original steady states following by a disruptive event, and more importantly preparing for unexpected events, responding to disruptions, and recovering from disruptive events to continue its operations. Christopher and Lee (2004) addressed the role of suppliers in creating resilient supply chains and emphasized on the necessities of collaborative relationship with suppliers. The authors concluded that the risk mitigation is possible when suppliers have collaboration with each other with high visibility. Zsidisin and Smith (2005) and Wu et al. (2010) introduced four factors including vulnerability, collaboration, risk awareness, and supply chain continuity management that contribute to the supplier's risk reduction.

In this section, we aim to identify contributors to the resilient supplier based on resilience capacity of supplier. We define the resilience capacity of a supplier as its capability to withstand vigorously against disruptive events by utilizing its absorptive capacity and adopt itself to new disrupted condition by utilizing adaptive capacity as the second defense line and recover its lost capacity by its restorative capacity as the final defense line. In a simple word, we divide the resilience capacity of supplier into three capacities: absorptive capacity, adaptive capacity and restorative capacity. Absorptive capacity refers to the degree to which a supplier can absorb the shocks of disruptive event and minimize the negative consequences with minimum levels of efforts. In fact, absorptive capacity can be referred as pre-disaster resilience for a supplier. We identified five contributors to absorptive capacity of supplier that could eventually enhance the supplier's resilience. These contributors are following as below:

- *Surplus inventory*: keeping a surplus of raw material and components can help a supplier overcome a supply-chain disruption. Although keeping extra inventory increases inventory holding cost but at the same time could help to continue to supply manufacturers under disruption circumstances while disrupted supplier return to its steady state.
- *Location separation*: natural disasters are the most common disruptions to suppliers that could cause devastating consequences to the performance of suppliers, as addressed in "Introduction" section. Many of electronic components of PC companies are being supplied by Japanese suppliers. Many of Japanese suppliers are exposed to natural disasters, especially earthquakes. Purchasing raw material from a supplier that is geographically separated from natural disasters could potentially reduce the likelihood that a regional disaster will negatively impact the supply process of a supplier.
- *Backup supplier contracting*: suppliers may contract with a backup supplier to overcome the shortage of supplied capacity in the case of disruption. It is important for a supplier to find and contract with a suitable backup supplier in advance.
- *Robustness/physical protection*: physical protection of supplier's building and facilities could decreases negative impact of disruption, especially in the case of natural disasters. Physical protection strategies can be referred as contributor to robustness of supplier against disruption.
- *Reliability*: reliability of a supplier reflects its ability to consistently supply an acceptable raw material or product at the required time. It is obvious that supplier with higher reliability are less susceptible to disruptions. Hence, it is important for suppliers to fortify their reliability in order to decrease the impact of disruption consequences.

Adaptive capacity is the second line of defense for suppliers and can be applied when absorptive capacity is not capable enough of absorbing the shocks of disruptions. Absorptive capacities are the temporary solutions that sup-

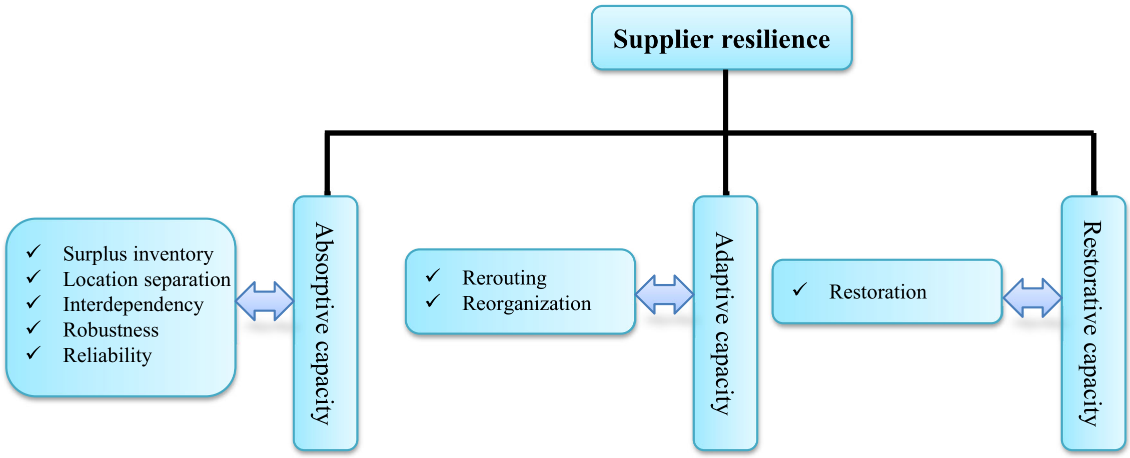


Fig. 1 Eight contributors to the supplier resilience

plier can utilize to adopt itself in the case of disruptions. The contributors to the adaptive capacity are detailed below:

- *Rerouting*: suppliers are generally more resilient if they can use different transportation modes in the case of disruptions. Rerouting options under disruptive event can enhance the s resiliency of supplier but usually is more expensive than the original transshipment mode.
- *Reorganization*: suppliers affected by a disruptive event may pool resources to lessen the impact. Suppliers may normally be prohibited from collaboration with their competitive ones; however temporary collaboration can enhance the resilience of disrupted supplier in the case of disasters.

Restorative capacity is the last line of defense for a supplier that reflects the capability of that supplier to repair or restore its damaged facilities and equipment efficiently. Restorative capacity refers to the repair or restoration activities that could bring the capacity of damaged supplier into its normal operating state.

The aforementioned contributors to the supplier resilience are schematically illustrated in Fig. 1. To elaborate the impact of resilience notion on supplier selection, we graphically sketched a causal relationship diagram which represents how the contributors to the resilient supplier can enhances its resiliency and also its interaction with other attributes of suppliers such its costs and lead time. As illustrated in Fig. 2, the related elements are represented through a polarity, either positive (+) or negative (−) to indicate how independent element changes when the interdependent variable changes. For example, relationship between rerouting and adaptive capacity is represented by a positive link which reflects that implementing rerouting option can enhances the adaptive capacity of supplier. The resilience cost of supplier can be viewed as sum of pre-disaster resilience cost and post-disaster resilience cost. As shown in Fig. 2, absorptive capacity of supplier contributes to the pre-disaster cost while adaptive and restorative costs are contributed into the post-disaster resilience cost.

It is noteworthy to remark that ability of supplier to mitigate a disruptive event is highly depends on the type and intensity of disruptive event. In this paper, natural disaster is considered as the major source of disruptions to the supplier. Subsequently, absorptive capacity of supplier is constructed based on the type of disruptive event. However, in the future research we aim to investigate the other types of disruptions that may impact on the performance of supplier including labor strike, exchange rate fluctuations, or even global financial crises.

Literature to supplier selection

Various methods have been proposed to deal with supplier selection problem including multi-attribute decision making (MADM) techniques, mathematical programming, and artificial intelligence, among others. Hang Hong et al. (2005) proposed a mathematical programming model that accounts the change in suppliers' supply capabilities and customer needs over a period of time. The proposed model does not only maximize revenue but also satisfies customer needs. The proposed model is applied to supplier selection and management of the agriculture industry in Korea. Pi and Low (2005) used Taguchi loss functions for supplier evaluation and selection. Four attributes including quality, on-time delivery, price, and service are considered in their paper. These four attributes transformed to the quality loss and combined to one decision variable for decision making. Wang and Che (2007) presented an integrated model for modeling the change of behavior of product parts and for assessing alternative suppliers for each part by using fuzzy theory, genetic algorithm and T-transformation technology. Farzipoor Saen (2007) proposed an imprecise development analysis (IDEA) in the

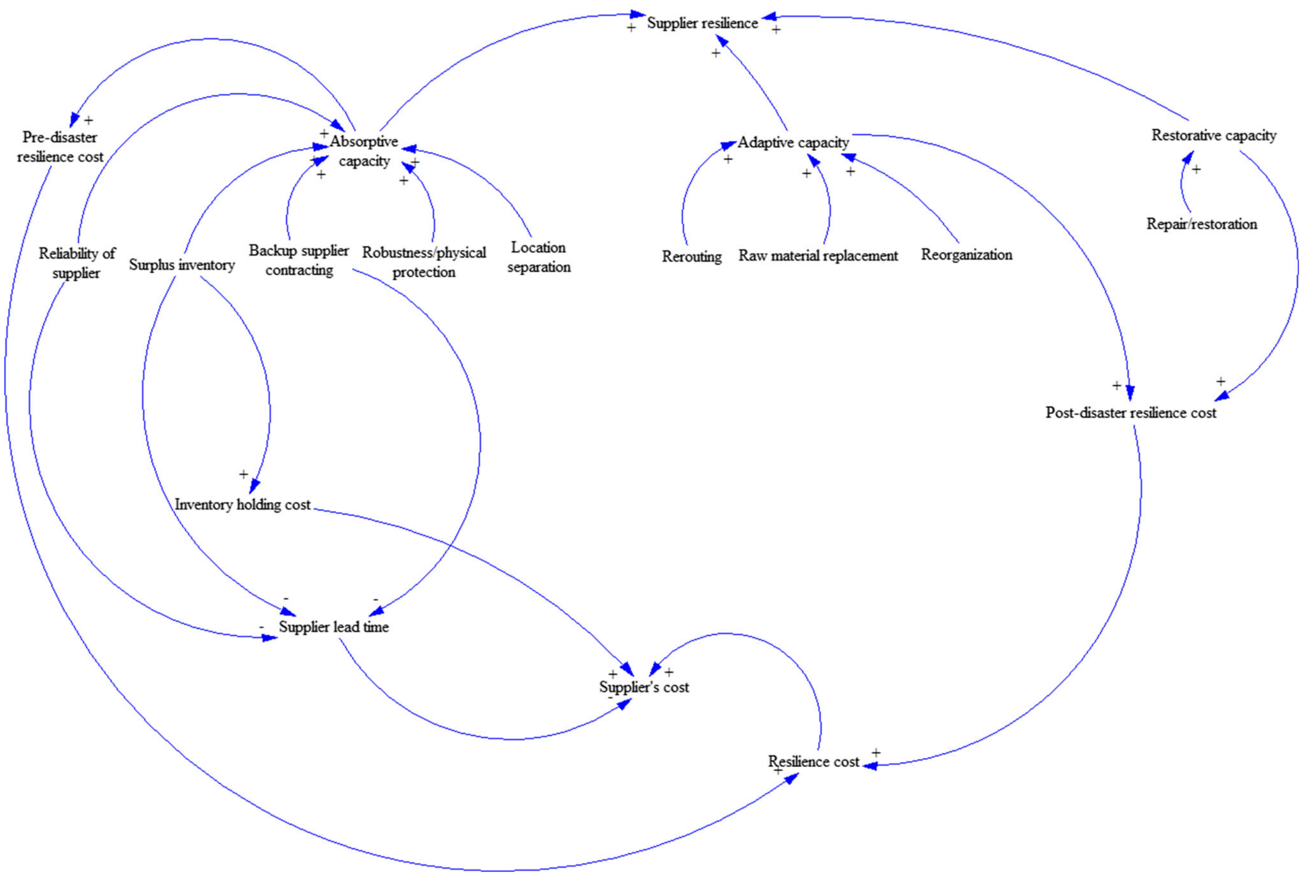


Fig. 2 The causal relationship diagram of contributors to the supplier resilience

presence of both cardinal and ordinal data. The results of this paper were used from both a buyer's and supplier's perspective. Gencer and Gurpinar (2007) applied analytic network process (ANP) to evaluate the relationship between supplier selection criteria. The proposed model is implemented in an electronic company. Li et al. (2008) proposed a grey-based rough set approach to deal with supplier evaluation in supply chain management. Their proposed approach takes advantage of mathematical analysis power of grey system. Kang et al. (2010) proposed a fuzzy ANP model for evaluating the performance of suppliers with a case study of IC packing company selection in Taiwan. Liao and Kao (2011) combined fuzzy technique for order preference by similarity ideal solution (TOPSIS) and multi-choice goal programming (MCGP) to solve the supplier selection problem. The major advantage of their method is that it allows decision makers to multiple aspiration levels for supplier selection problems. Kilincci and Onal (2011) employed fuzzy AHP for supplier selection in a washing machine company. Karsak and Dursun (2014) introduced an approach based on integrating quality function deployment (QFD) and data envelopment analysis (DEA) for selecting best supplier among supplier alternatives. The main feature of their method is to allow for considering the influences of inner dependence among supplier assessment criteria through constructing a house of quality (HOQ). Deng and Chen (2011) proposed a methodology based on using fuzzy set theory and Dempster–Shafer theory to deal with supplier selection problem. Igoulalene et al. (2015) proposed a fuzzy hybrid multi-criteria decision making approach for solving supplier selection problem. Their proposed approach is based on combining fuzzy consensus-based possibility measure and fuzzy TOPSIS. Kumar Kar (2014) proposed an approach based on integrating fuzzy AHP and fuzzy goal programming for the supplier selection problem. Lee et al. (2014) combined TOPSIS and AHP based on the fuzzy theory to determine the prior weights of criteria and select the best-fit suppliers by taking subjective vague preferences of decision making into account. You et al. (2015) developed a new multi-criteria decision making model based on using interval 2-tuple linguistic variables and extended VIKOR approach to select the best supplier under uncertainty and incomplete information environment. Dalalah et al. (2011) adjusted DEMATEL to deal with fuzzy rating and assessments by converting the relationship between causes and effects of the criteria into an intelligible structural model. Deng et al. (2014) represented a new form of representation for uncertain information involved with supplier selection problem, called D numbers. The authors then applied a D-

AHP method for the supplier selection problem. Sanayei et al. (2008) integrated multi-attribute utility theory (MAUT) and linear programming for rating and selecting the best suppliers and defining the optimal order quantities among the selected suppliers in order to maximize the total additive utility. Fazlollahtabar et al. (2011) proposed a multi-objective mixed integer programming for supplier selection problem. Their objective aimed to minimize the total costs of supplier including (holding cost, order cost, inventory) cost, total defect rate, total penalized earliness and tardiness, and total value of purchase. The authors then used AHP to determine the weight associated with each objective function. Beikkhakhian et al. integrated fuzzy TOPSIS-AHP methods for evaluating agile supplier selection criteria and ranking of suppliers. Sawik (2013) proposed a mixed integer linear programming for selection of resilient supply portfolio under disruption risks. The objective of their model is to achieve a minimum cost of suppliers protection, emergency inventory pre-positioning, parts ordering purchasing, transportation and shortage to mitigate the impact of disruption risks (Sawik 2013). Rajesh and Ravi (2015) applied grey relational analysis approach for supplier selection in resilient supply chains. Four attributes of supplier's performance factors (quality, cost, and flexibility), supplier's responsiveness (supply chain velocity, and supply chain visibility), supply risk reduction (vulnerability, collaboration, risk awareness, and supply chain continuity management), supplier's technical support (technical capability, and R&D), supplier's sustainability (safety, and concern for environment) are taken into account. Torabi et al. (2015) developed a two-stage stochastic programming model to address supplier selection and order allocation problem to build the resilient supply chain. Their model accounts for proactive resilient strategy including fortification of suppliers, contracting with backup suppliers to enhance the resilience level of the selected supply base.

Analyzing the literature of supplier selection problem shows that various methodologies have been used. Generally speaking, there are four main methodologies for evaluating and selecting suppliers: i) multi-criteria decision making methods which include AHP, ANP, TOPSIS, VIKOR, etc., ii) mathematical modeling methods which include mixed-integer linear programming (MILP), multi-objective programming (MOP), DEA, etc., iii) artificial intelligence methods which include neural network, Bayesian networks, fuzzy logic, etc., and finally iv) integrated approaches which includes combining of any two or more supplier selection methods such as integrated AHP and TOPSIS, etc.

Resilience prediction model

In order to obtain better resilience prediction based on the historical data, a robust machine learning technique, known as ensemble method, is proposed. It leverages the power of multiple models to achieve better prediction accuracy than any of the individual models could on their own. The basic goal when designing an ensemble method is same as when establishing a committee of people: each member of the committee should be as competent as possible, but the members should be complementary to one another.

Two of the most popular ensemble learning algorithms are Bagging and Boosting. Bagging generates multiple bootstrap training sets from the original training set and uses each of them to generate a classifier for inclusion in the ensemble. Boosting involves incrementally building an ensemble by training each new model instance to emphasize the training instances that previous models misclassified. In some cases, boosting has been shown to yield better accuracy than bagging, but it also tends to be more likely to over-fit the training data. By far, the most common implementation of Boosting is AdaBoost. AdaBoost generates a sequence of base models with different weight distributions over the training set.

The basic steps of analytical model development process including ensemble method are shown in Fig 3. The procedure starts with reading the raw input data, followed by cleaning the data using data auditing and feature selection process. These steps provide basic statistics and importance of individual variable based on the input data. Next steps include data exploration by applying exploratory data analysis (EDA), data transformation to derive (if any) meaning new variables using the existing variables, and partitioning the data into training (model development) and testing datasets (validating the developed model). Finally, models are developed using different machine learning algorithms (logistic regression, CART, neural network, etc.), followed by combing them into a single ensemble model and using this ensemble model for scoring and implementation.

In this paper, an ensemble method combining logistic regression, CART, and neural network is proposed to predict the resilience of the suppliers.

Logistic regression

Logistic regression, also called nominal regression, is a statistical technique for classifying records based on values of input fields. It is analogous to linear regression but takes a categorical target field instead of a numeric one. Logistic regression can be binomial or multinomial. Binomial logistic regression deals with targets with two discrete categories (e.g., "win" vs. "loss"). Multinomial logistic regression deals with targets with more than two categories (e.g., "disease A" vs. "disease B" vs. "disease C").

It works by building a set of equations that relate the input field values to the probabilities associated with each of the output field categories. For example, we have a binary output variable Y, and we want to model the conditional probability

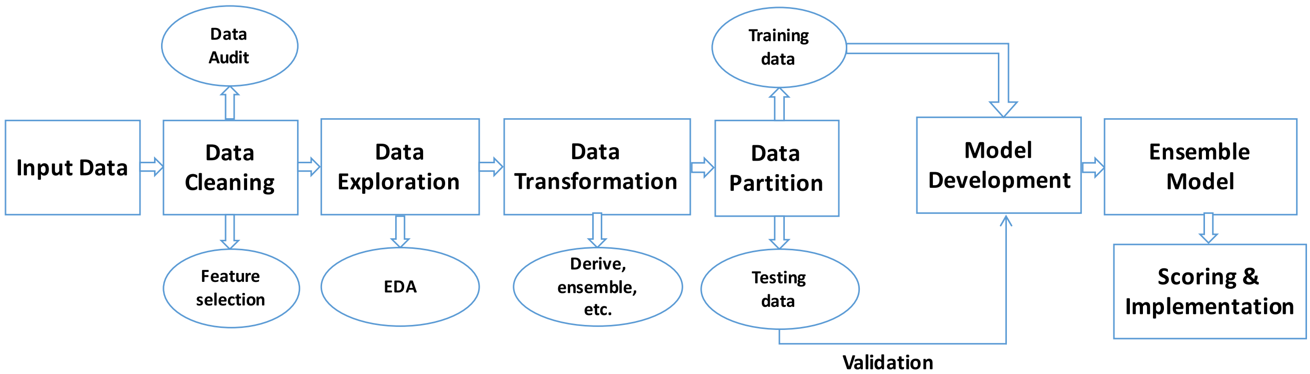


Fig. 3 Basic steps of predictive model development process

$p(Y=1|X=x)$ as a function of x; any unknown parameters in the function are to be estimated by maximum likelihood. Formally, logistic regression model is,

$$\log \frac{p(Y=1|X=x)}{1-p(Y=1|X=x)} = \beta_0 + x\cdot\beta \quad (1)$$

Solving for p, this gives,

$$p\left(Y=1|X=x\right) = \frac{e^{\beta_0+x\cdot\beta}}{1+e^{\beta_0+x\cdot\beta}} = \frac{1}{1+e^{-(\beta_0+x\cdot\beta)}} \quad (2)$$

To generalize the logistic regression model with K classes of output variable Y as a function of x, the model for the conditional probability $Pr(Y=K-1|X=x)$,

$$\log \frac{p(Y=K-1|X=x)}{p(Y=K|X=x)} = \beta_{(K-1)0} + \beta_{K-1}^T x \quad (3)$$

A simple calculation shows that,

$$p\left(Y=k|X=x\right) = \frac{e^{\beta_{k0}+\beta_k^T x}}{1+\sum_{l=1}^{K-1} e^{\beta_{l0}+\beta_l^T x}}$$
$$= \frac{1}{1+\sum_{l=1}^{K-1} e^{-(\beta_{l0}+\beta_l^T x)}}, k=1,2,\ldots K-1 \quad (4)$$

Once the model is generated, it can be used to estimate probabilities for new data. For each record, a probability of membership is computed for each possible output category. The target category with the highest probability is assigned as the predicted output value for that record.

Classification and regression tree (CART)

CART generates a decision tree that allows predicting or classifying future observations. It partitions the feature space into a set of rectangles, and then fit a simple model (like a constant) in each one. Let's consider a regression problem with continuous response Y and inputs $x \in R_m$, each taking

INITIALIZE	All cases in the root node.
REPEAT	Find optimal allowed split.
	Partition leaf according to split.
STOP	Stop when pre-defined criterion is met.

Fig. 4 Recursive partitioning process

values in the unit interval. We first need to split the space into two segments, and model the response by the mean of Y in each region. We choose the variable and split-point to achieve the best fit. Then one or both of these regions are split into two more regions, and this process is continued, until some stopping rule is applied. The common method used to split the space is recursive partitioning where training records are split into segments by minimizing the impurity at each step, where a node in the tree is considered "pure" if 100 % of cases in the node fall into a specific category of the target field. The algorithm for recursive partitioning is shown in Fig. 4.

The corresponding regression model predicts Y with a constant C_m in region R_m, that is,

$$F\left(x\right) = \sum_{m=1}^{M} C_m I\left(x\in R_m\right) \quad (5)$$

where, $\{R_m\}_1^M$ are subregions of the input variable space, C_m are the estimated values of the outcome, and x is a vector of input variables.

CART tries to minimize,

$$e(T) = \sum_{i=1}^{N} \left[Y_i - \sum_{m=1}^{M} C_m I\left(x\in R_m\right)\right]^2 \quad (6)$$

with respect to C_m and R_m.

Different measures of impurity in classification include deviance, entropy, and GINI index. Consider, at each node i of a classification tree we have a probability distribution p_{ik}

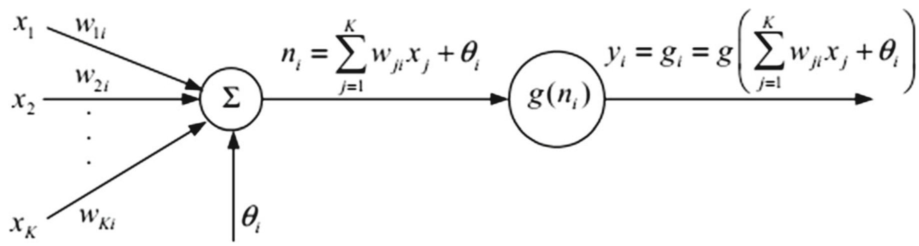


Fig. 5 Single node in a MLP network (Koivo 2008)

over the k classes. We observe a random sample n_{ik} from the multinomial distribution specified by the probabilities p_{ik}. The impurity measures are defined as below:

Deviance: $D = \sum_i D_i$, $where\ D_i = -2\sum_k n_{ik} \log p_{ik}$
Entropy: $\sum_k p_{ik} \log p_{ik}$
GINI index: $\sum_{j \neq k} p_{ij} p_{ik} = 1 - \sum_k p_{ik}^2$

Again, for regression trees we use the residual sum of squares,

Residual sum of squares: $\sum_{cases\ j} \left(Y_i - \mu_{[j]}\right)^2$

Target and input fields can be numeric ranges or categorical (nominal, ordinal, or flags); all splits are binary (only two subgroups).

Neural network

A neural network is a simplified model of the way the human brain processes information. It works by simulating a large number of interconnected processing units that resemble abstract versions of neurons. The processing units are arranged in layers. Neural networks consist of a large class of different architectures. The most useful neural networks in function approximation are Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) networks (Koivo 2008). A MLP consists of an input layer, several hidden layers, and an output layer. Node i, also called a neuron, in a MLP network is illustrated in Fig. 5. It includes a summer and a nonlinear activation function g.

The inputs $x_k, k = 1, 2, \ldots, K$ to the neuron are multiplied by weights w_{ki} and summed up together with the constant basis term θ_i. The resulting n_i is the input to the activation function g. The activation function was originally chosen to be a relay function, but for mathematical convenience a hyperbolic tangent (*tanh*) or a sigmoid function are most commonly used (Koivo 2008). The output of node i represented in Fig. 5 can be written as follows:

$$y_i = g_i = g\left(\sum_{j=1}^{k} w_{ji} x_j + \theta_i\right) \tag{7}$$

A MLP network can be constructed by connecting several nodes in parallel and series. A typical MLP network with single hidden layer is shown in Fig. 6.

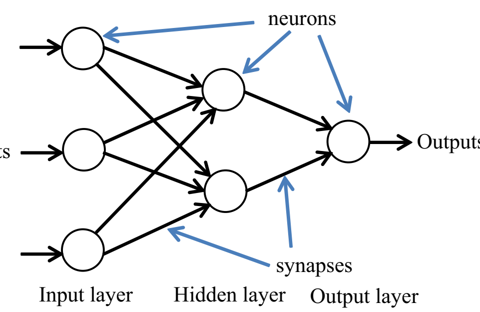


Fig. 6 A MLP network with single hidden layer

As shown in Fig. 6, we input our features (x_1, x_2 and x_3) in the input layer. The *output layer* has the neuron that outputs the final value computed by a hypothesis $h_\Theta(x)$. The layer in between is called the *hidden layer* and there may be more than one hidden layer. Basically, anything that isn't an input layer or an output layer is called a hidden layer. To explain the specific computations represented by a neural network, let us denote $a_i^{(j)}$ be the activation of neuron (or unit) i in layer (j). Activation refers to the value that is computed by a specific sigmoid. In addition, a neural network is parameterized by the matrices $\Theta^{(j)}$ each $\Theta^{(j)}$ is a matrix of weights controlling the function mapping from layer j to the next layer, layer $j + 1$. The computations represented by the diagram in Fig. 6 are

$$\begin{aligned} a_1^{(2)} &= g\left(\Theta_{11}^{(1)} x_1 + \Theta_{12}^{(1)} x_2 + \Theta_{13}^{(1)} x_3\right) \\ a_2^{(2)} &= g\left(\Theta_{21}^{(1)} x_1 + \Theta_{22}^{(1)} x_2 + \Theta_{23}^{(1)} x_3\right) \\ h_\Theta(x) = a_1^{(3)} &= g\left(\Theta_{11}^{(2)} a_1^{(2)} + \Theta_{12}^{(2)} a_2^{(2)}\right) \end{aligned} \tag{8}$$

where, $g(\cdot)$ is the sigmoid or logistic activation function, applied to a linear combination of its inputs.

Analytic hierarchy process (AHP)

AHP is a structured technique for dealing with multi-criteria decision making problems (Saaty 1980). Both quantitative and qualitative criteria can be integrated by using AHP in the decision-making process.

Generally speaking, the process of AHP method can be split into three steps. First, construct a hierarchical structure by

Table 2 Numerical rating in the AHP method

Scale	Meaning
1	Equal importance
3	Moderate importance
5	Strong importance
7	Demonstrated importance
9	Extreme importance
2, 4, 6, 8	Importance value

Table 3 Random consistency index $R.I$

n	1	2	3	4	5	6	7	8	9	10
$R.I.$	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

recursively breaking down the decision problem. Second, establish the pairwise comparison matrix to indicate the relative importance of alternatives. A numerical rating as shown in Table 2 is suggested. Third, compute the priority weights of alternatives in according to the pairwise comparison matrix by the following equation:

$$Aw = \lambda_{max} W, \quad W = (W_1, W_2, \ldots, W_n)^T \tag{9}$$

where A is a n dimensional comparison matrix, λ_{max} is the largest eigenvalue of A, and w is the eigenvector corresponding to λ_{max}.

In AHP, an index named consistency index ($C.I.$) is used to measure the amount of inconsistency within the pairwise comparison matrix A.

$$C.I. = \frac{\lambda_{max} - n}{n - 1} \tag{10}$$

Accordingly, the consistency ratio $C.R.$ is used to measure the degree of $C.I.$ by the following equation:

$$C.R. = \frac{C.I}{R.I} \tag{11}$$

where $R.I.$ is the random consistency index, its value is dependent on the dimension of the matrix, listed in Table 3. If $C.R. < 0.10$, then the inconsistency degree of the comparison matrix A is acceptable and the eigenvector w can be used as the weighting vector after normalization. Otherwise, the comparison matrix must be adjusted.

Note that fuzzy AHP can be also used to create weights for man and evaluation criteria under uncertainty environment.

The proposed hybrid ensemble-AHP approach

The proposed hybrid approach for resilient supplier selection consists of three following phases as given in Fig. 7.

Phase 1: *Identifying contributors to the resilient supplier selection*

In the first phase, the contributors to the resilient suppliers are identified and grouped along with primary (traditional) supplier selection criteria. Then the hierarchy structure is formed such that the objective (resilient supplier selection) is at the first level, four primary criteria including cost, quality, lead time, and response rate are considered along with resilience criteria which includes sub-criteria of surplus inventory, location separation, backup supplier contracting, robustness, reliability, rerouting, reorganization, repair/restoration. The hierarchy of resilient supplier selection is illustrated in Fig. 8.

Phase 2: *Calculating the resilience value of suppliers by using ensemble method*

After forming a decision hierarchy, the resilience value of suppliers must be determined. A robust machine learning technique consisting of logistic regression, CART and neural network have been employed to calculate the resilience value of suppliers. Based on the data collected on three major resilience capabilities of the suppliers and their past delivery performances, a combined predictive model called ensemble model is developed. The superiority of ensemble model is presented in "Case study" section.

Phase 3: *Selecting top suppliers using AHP*

In the third phase, the top five suppliers in terms of resilience value found in second phase are selected as alternatives for the evaluation purpose. The AHP approach is used to evaluate and rank the five suppliers.

Case study

To illustrate the applicability of the developed approach, a real case of supplier selection is studied in this paper. A reputed plastic pipe manufacturer which produces water and sewage plastic pipes in USA is selected for this study. The company is committed to manufacture high quality water and sewage plastic pipes with on time delivery and reasonable cost. The manufacturer uses PVC raw material to make water and sewage pipes. The PVC raw material must be imported in a massive scale from abroad. The pipe manufacturer has experienced several production disruptions due to shortage of PVC raw materials mainly because of supply disruptions in the past. Since the raw material must be imported from abroad, ensuring on-time supply without disruption has become the primary concern for the manufacturer.

The manufacturer found hundreds of alternative raw material suppliers that could be potentially selected for collaboration. The data related to the primary criteria and resilience sub-criteria are collected through procurement department through questionnaire distributed among suppliers. The employee of procurement department also utilized

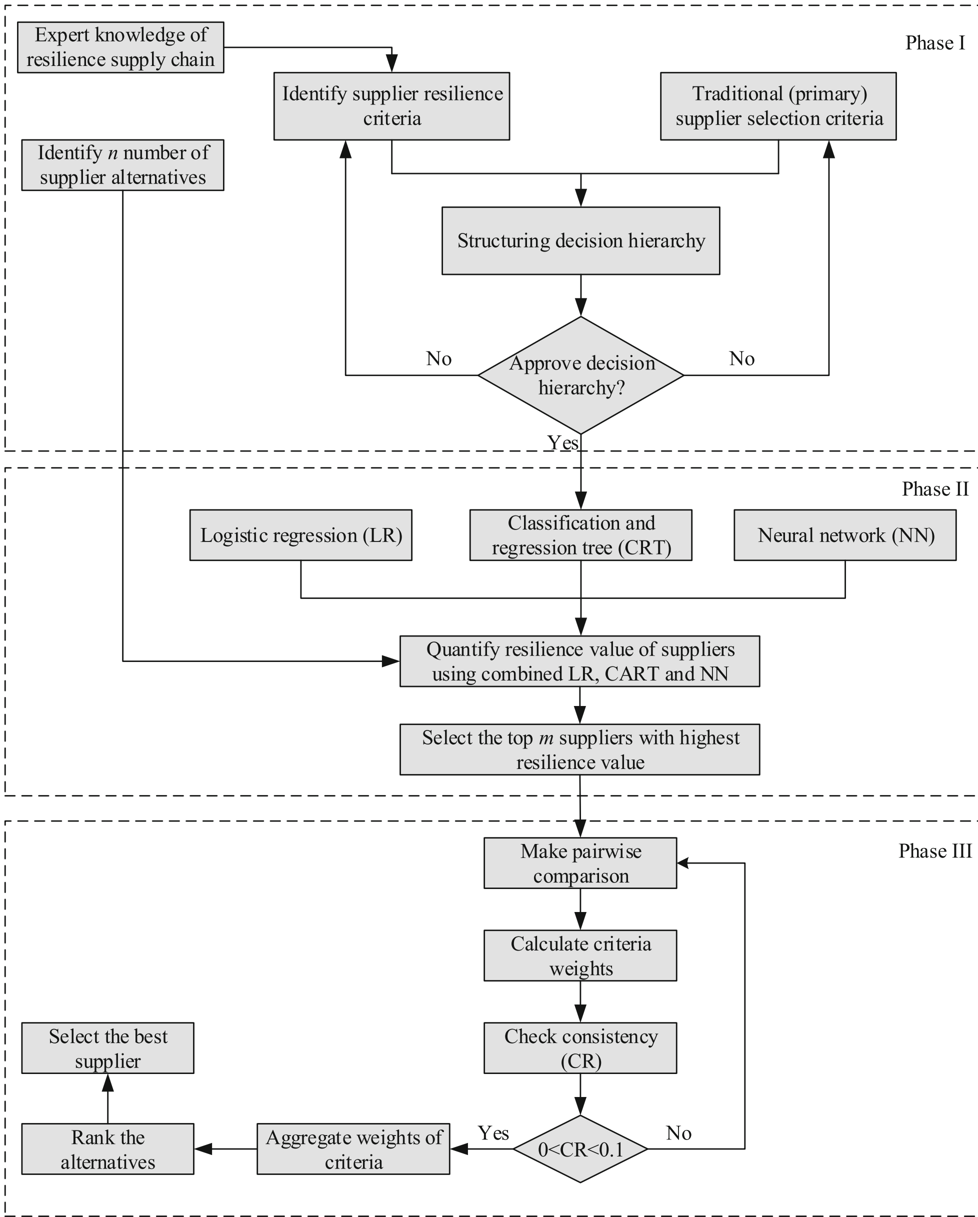


Fig. 7 Proposed hybrid ensemble-AHP approach for resilient supplier selection

information provided through the Plastic Industry Trade Association (WWW. resource 1), and Alibaba (WWW. Resource 2). The proposed ensemble approach is employed to find the top five suppliers with highest resilience value.

Resilience prediction model

An ensemble method comprising three different machine learning algorithms—logistic regression, CART, and neural network, has been implemented using commercial data mining software SPSS modeler. As mentioned earlier, ensemble method provides better prediction accuracy by leveraging the power of multiple models. The developed model utilized the data of one hundred suppliers with their attributes and past performances. Using the proposed ensemble model, the suppliers are scored based on their attributes (predictor variables). The following sub-sections briefly describe about the collected data, model development using SPSS modeler, model nodes, and their predictive accuracy (validation).

Data preparation

Table 4 shows the sample data for PVC raw material suppliers with their attributes and their past performances. It represents eight predictor variables for each supplier's resilience capabilities and value of corresponding binary response variable.

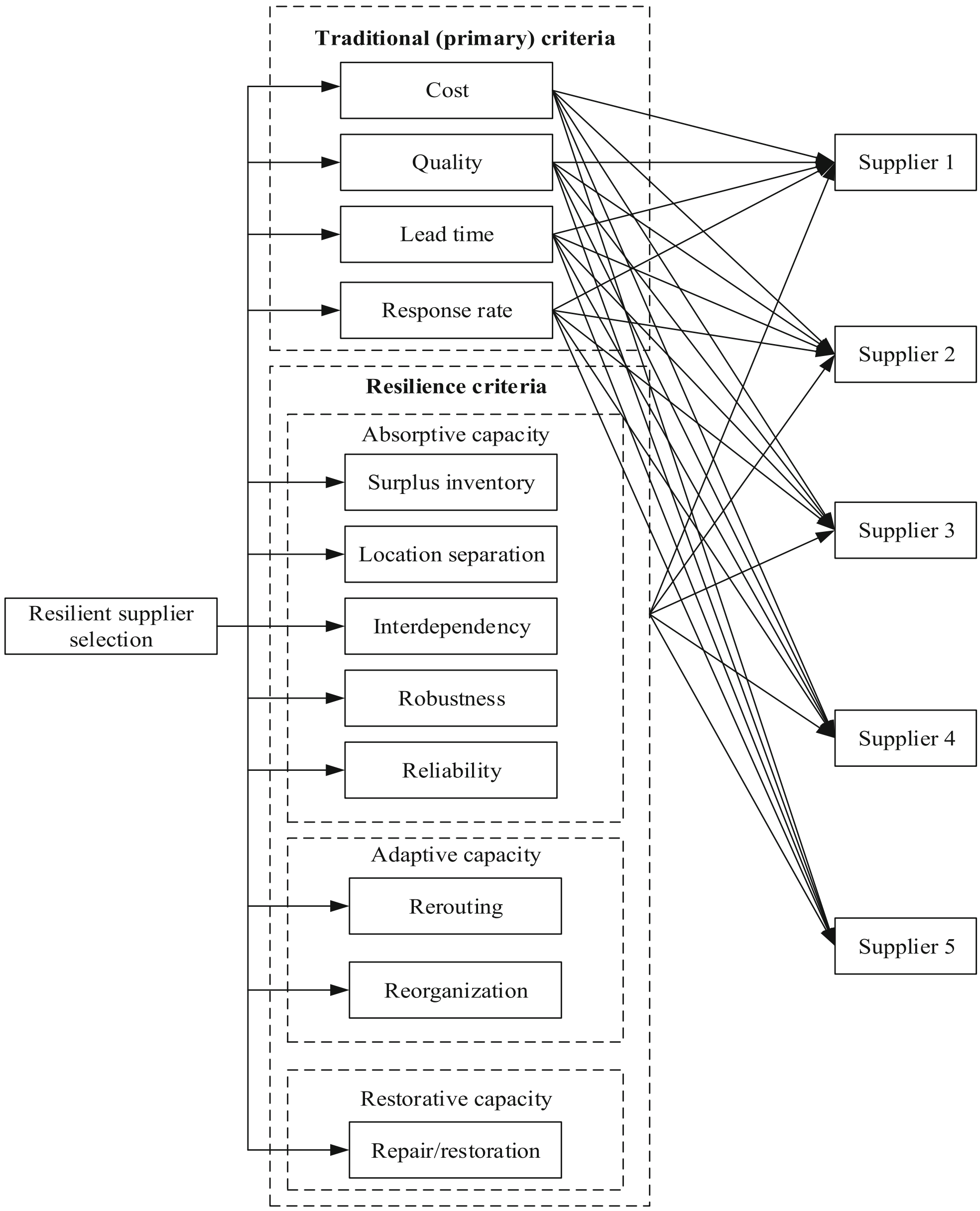


Fig. 8 Major criteria and their associated sub-criteria for the resilient supplier selection

Table 5 represents the data types for predictor and dependent variables. It shows there are primarily two different types of variables – ordinal (categorical) and binary. Among them, six predictors are ordinal variables and three binary variables including the response variable. Ordinal variable is a special type of categorical variable, where the order matters but not the difference between values. For example, you might ask students to express the level of satisfaction they had after taking a class on a scale of 1 to 10. A score of 7 means more satisfied than a score of 5, and that is more than a score of 3. In this paper, all the ordinal variables have 5 levels; these represent very low, low, medium, high, and very high levels. Since the response variable is a binary, it is required to apply some classification algorithms to develop predictive models. Three different classification models—logistic regression, CART, and neural network are used to develop the robust ensemble model.

Model development

The model stream, developed in SPSS modeler, is shown in Figs. 9 and 10. Model stream in Fig. 9 shows individual models—logistic regression, CART, and neural network, whereas Fig. 10 shows the ensemble model comprising these three models to circumvent the drawbacks of the individual

Table 4 Sample input data

Supplier	X1	X2	X3	X4	X5	X6	X7	X8	Y
Ahmedabad, India	2	3	0	1	1	0	2	2	0
Beijing, China	5	5	1	3	4	1	3	3	1
Daegu, South Korea	2	2	0	2	2	0	1	2	0
Delhi, India	5	2	1	4	4	1	4	5	1
Fujian, China	4	3	1	3	5	1	5	3	1
Guangdong, China	1	2	0	1	3	0	2	2	0
Gujarat, India	4	3	1	5	3	1	5	4	1
Gyeonggi-do, South Korea	1	2	0	1	3	0	2	1	0
Ha Noi, Vietnam	4	2	1	3	4	1	3	4	1
Hanoi city, Vietnam	5	4	1	4	3	1	5	3	1
Ho Chi Minh City, Vietnam	4	5	1	5	5	1	4	5	1
Ho Chi Minh, Vietnam	3	1	0	1	2	0	2	1	0
Hong Kong	5	4	1	5	4	1	3	4	1
Hong Kong	3	2	1	4	5	1	5	5	1
Hunan, China	2	3	0	3	2	0	1	1	0
Jiangsu, China	2	1	0	2	1	0	2	3	0
Jiangxi, China	3	3	1	4	4	0	4	5	1
Maharashtra, India	1	2	0	1	2	0	1	1	0
Seoul, South Korea	2	1	0	3	1	1	3	1	0
Shaanxi, China	3	4	1	4	5	1	2	4	1
Shandong, China	5	5	1	5	3	1	3	4	1
Shanghai, China	5	4	1	4	3	1	3	4	1
Sichuan, China	2	2	0	3	2	1	1	1	0
Taiwan	5	4	1	3	3	1	3	3	1
Taiwan	4	5	1	2	3	1	4	5	1
Taiwan	4	2	1	5	3	1	3	5	1
Taiwan	1	1	0	1	1	0	2	1	0
Tamil Nadu, India	1	1	0	2	3	0	2	1	0
Tianjin, China	4	5	1	4	4	1	4	4	1
Zhejiang, China	5	3	1	3	5	1	5	5	1

Table 5 Input data types

Name	Type	Range
Surplus inventory (X1)	Ordinal	1, 2, 3, 4, 5
Location separation (X2)	Ordinal	1, 2, 3, 4, 5
Backup supplier contracting (X3)	Binary	0,1
Robustness (X4)	Ordinal	1, 2, 3, 4, 5
Reliability (X5)	Ordinal	1, 2, 3, 4, 5
Rerouting (X6)	Binary	0,1
Reorganization (X7)	Ordinal	1, 2, 3, 4, 5
Restoration (X8)	Ordinal	1, 2, 3, 4, 5
Response/observation (Y)	Binary	0,1

model. Model stream in Fig. 9 represents the sequential flow of developing the model. The basic structure follows as reading input data, defining variable types, auditing the data to assess the basic statistics of each variable and checking the quality of the input data, partitioning the input data to divide into training and testing set, developing the desired model using training data set, evaluating or validating the developed model using testing data set, and finally scoring the testing data set. The development of ensemble model by connecting the validated models, further evaluating the ensemble model, and finally scoring the desired input data sets is graphically depicted in Fig. 10.

Developed predictive models

All three different classification models, developed using the training data set in SPSS modeler, are described in this section. The CART model which has the tree depth of five is illustrated in Fig. 11. The tree starts branching from variables X4, meaning robustness is the most important predictor. Then it follows restoration, reliability, reorganization, and surplus

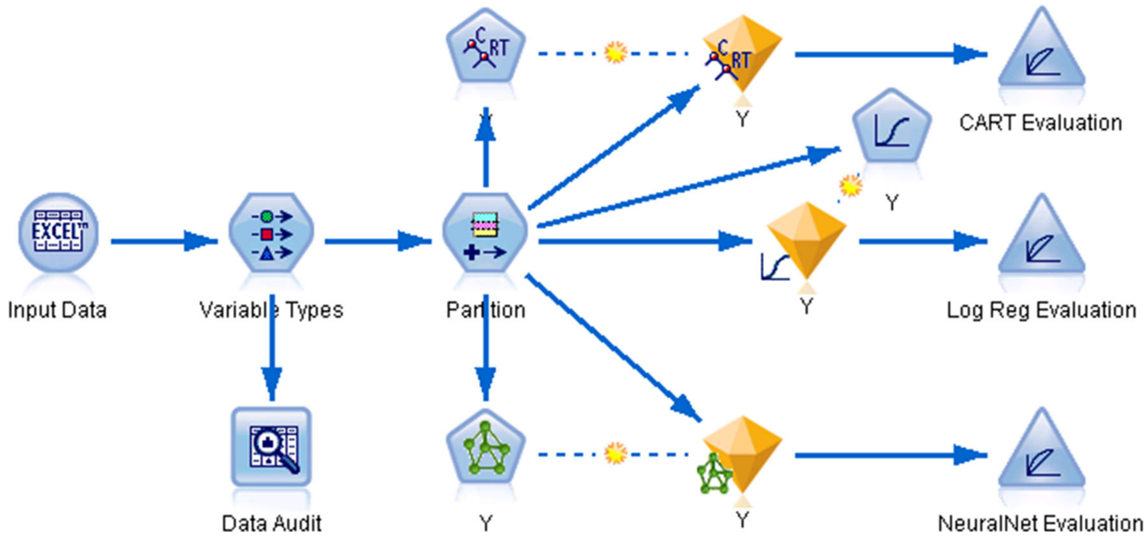


Fig. 9 Model stream in SPSS modeler of individual model

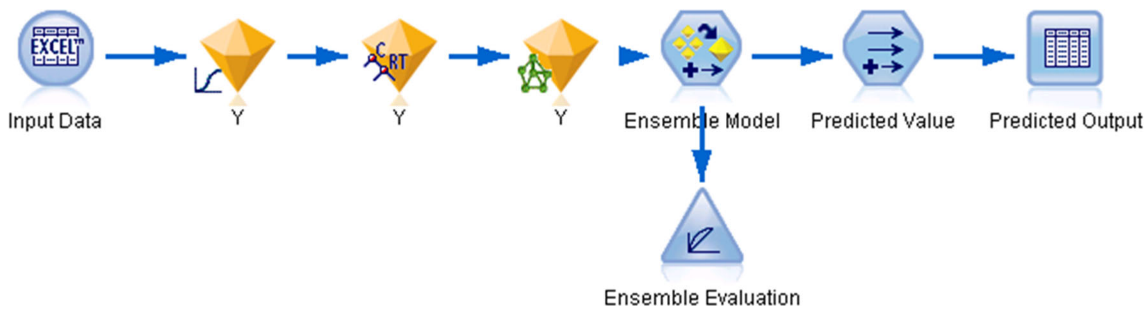


Fig. 10 Model stream in SPSS modeler of ensemble model

inventory. A total of eighteen different nodes are classified to predict each different segment of suppliers.

The logistic regression model parameter estimates and their significance in the model are presented in Table 6. Wald χ^2 statistics are used to test the significance of individual coefficients in the model, which calculated as follows:

$$W_j = \frac{B_j^2}{SE_{B_j}^2} \tag{12}$$

where B_j and SE_{B_j} are the value and standard error of coefficient j, respectively.

Table 6 shows the test for the coefficients of surplus inventory, restoration, reliability, reorganization, and robustness indicate that they contribute significantly in predicting resilience value of the suppliers.

Table 7 show the usefulness of overall model that are similar to the coefficient of determination (R^2) in linear regression. The Cox & Snell and the Nagelkerke R^2 are two such statistics and these values are 0.711 and 0.824, respectively. The Nagelkerke R^2 is an adjusted version of the Cox & Snell R^2, and therefore it is often preferred.

Finally, the logistic regression model with significant variables is given in equation below:

$$\begin{aligned}\log \frac{p(Y=1|X=x)}{1-p(Y=1|X=x)} &= 2.229 + (-0.4731) * [X1=1] \\ &+ (-0.3787) * [X1=3] + (-0.5481) * [X1=4] \\ &+ (-0.9727) * [X4=1] + (-0.7415) * [X4=2] \\ &+ (-0.9065) * [X4=3] + (-0.2133) * [X4=4] \\ &+ (-0.9773) * [X5=1] + (-0.496) * [X5=2] \\ &+ (-0.5127) * [X5=3] + (-0.9847) * [X5=4] \\ &+ (-0.2015) * [X7=1] + (-0.2916) * [X8=1] \\ &+ (-0.2876) * [X8=2] + (-0.338) * [X8=3]\end{aligned} \tag{13}$$

The graphical representation of the neural network model is shown in Fig. 12. It shows that between input and output layers, there are two hidden layers called neurons. In the first hidden layer, there are three neurons and there are two neurons in the second hidden layer. These neurons are

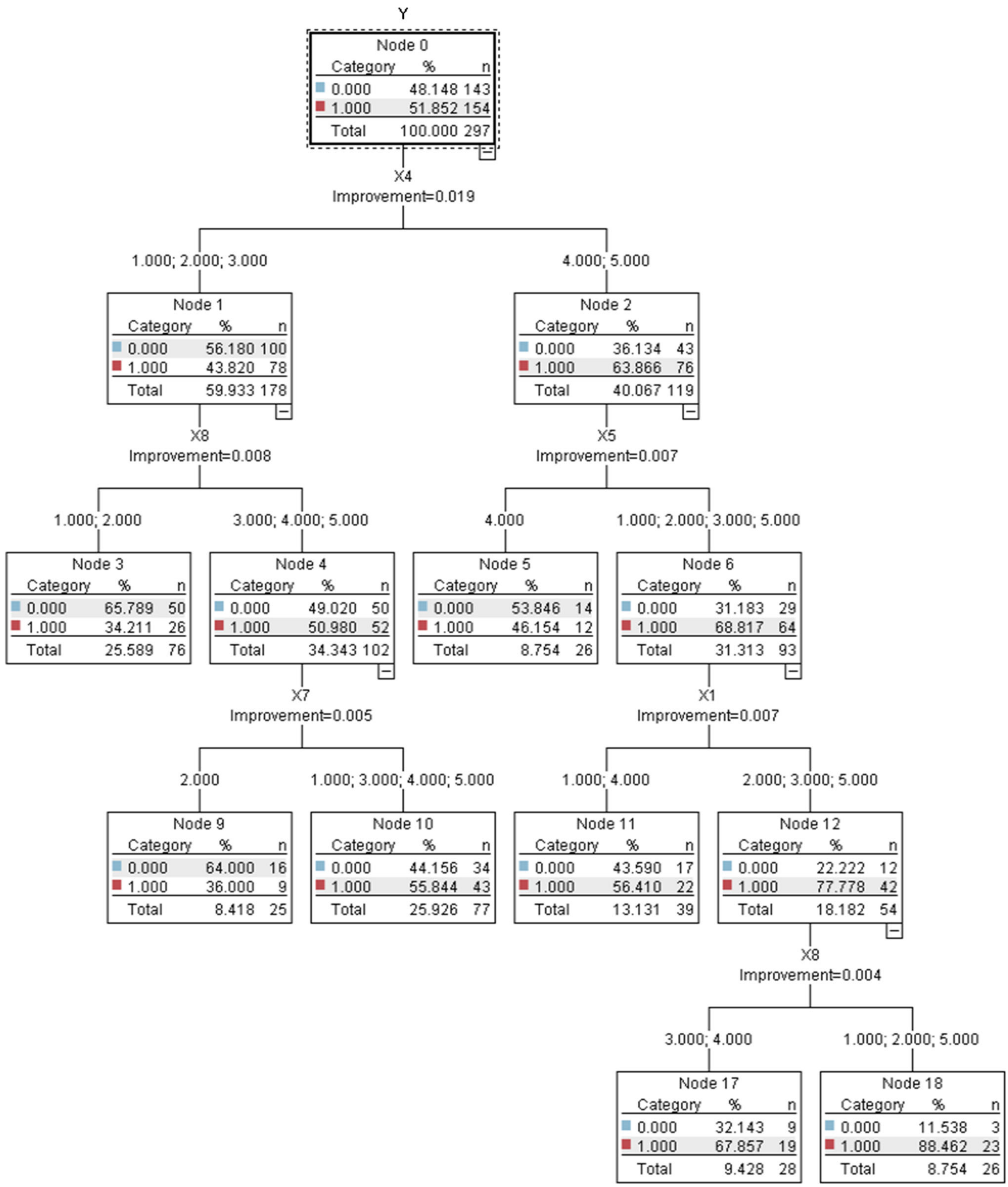


Fig. 11 SPSS modeler output for CART model

calculated based on the idea presented in "Neural network" section. The execution of neural network model suggests that the top three important predictors are robustness, reliability, and rerouting, in sequence as illustrated in Fig. 13.

Model evaluation

The ensemble model is evaluated to check its performance by creating gains chart, lift chart and receiver operating charac-

Table 6 Logistic regression output from SPSS modeler

Y(a)	Parameter	*B*	SE	Wald	df	Sig.	Exp (B)
1	Intercept	2.229	0.689	10.46602	1	0.001	
	[X1=1.000]	−0.473	0.138	11.748	1	0.001	0.623
	[X1=2.000]	0.006	0.005	1.44	1	0.225	1.006
	[X1=3.000]	−0.379	0.136	7.766058	1	0.009	0.685
	[X1=4.000]	−0.548	0.207	7.008425	1	0.01	0.578
	[X1=5.000]	0(*b*)	.	.	0	.	.
	[X2=1.000]	−0.505	0.38	1.766101	1	0.184	0.604
	[X2=2.000]	−0.639	0.396	2.603822	1	0.107	0.528
	[X2=3.000]	−0.512	0.393	1.697285	1	0.193	0.599
	[X2=4.000]	−0.306	0.396	0.597107	1	0.439	0.736
	[X2=5.000]	0(*b*)	.	.	0	.	.
	[X3=.000]	0.095	0.258	0.135584	1	0.713	1.099
	[X3=1.000]	0(*b*)	.	.	0	.	.
	[X4=1.000]	−0.973	0.428	5.168186	1	0.023	0.378
	[X4=2.000]	−0.741	0.381	3.782566	1	0.048	0.476
	[X4=3.000]	−0.907	0.405	5.015388	1	0.025	0.404
	[X4=4.000]	−0.213	0.129	2.726339	1	0.092	0.808
	[X4=5.000]	0(*b*)	.	.	0	.	.
	[X5=1.000]	−0.977	0.428	5.210766	1	0.023	0.376
	[X5=2.000]	−0.496	0.305	2.644622	1	0.095	0.609
	[X5=3.000]	−0.513	0.217	5.588757	1	0.021	0.599
	[X5=4.000]	−0.985	0.403	5.973961	1	0.015	0.374
	[X5=5.000]	0(*b*)	.	.	0	.	.
	[X6=.000]	−0.214	0.256	0.698792	1	0.403	0.807
	[X6=1.000]	0(*b*)	.	.	0	.	.
	[X7=1.000]	−0.202	0.118	2.93048	1	0.086	0.817
	[X7=2.000]	−0.027	0.021	1.653061	1	0.201	0.973
	[X7=3.000]	−0.064	0.408	0.024606	1	0.875	0.938
	[X7=4.000]	0.14	0.107	1.71194	1	0.196	1.15
	[X7=5.000]	0(*b*)	.	.	0	.	.
	[X8=1.000]	−0.292	0.127	5.286379	1	0.021	0.747
	[X8=2.000]	−0.288	0.133	4.689016	1	0.036	0.75
	[X8=3.000]	−0.338	0.141	5.746391	1	0.013	0.713
	[X8=4.000]	−0.025	0.185	0.018262	1	0.748	0.975
	[X8=5.000]	0(*b*)	.	.	0	.	.

a. The reference category is: 0.0.
b. This parameter is set to zero because it is redundant

Table 7 Model summary from SPSS modeler

Pseudo R-square	Value
Cox and Snell	0.711
Nagelkerke	0.824

teristic (ROC) curve. These methods are briefly summarized below.

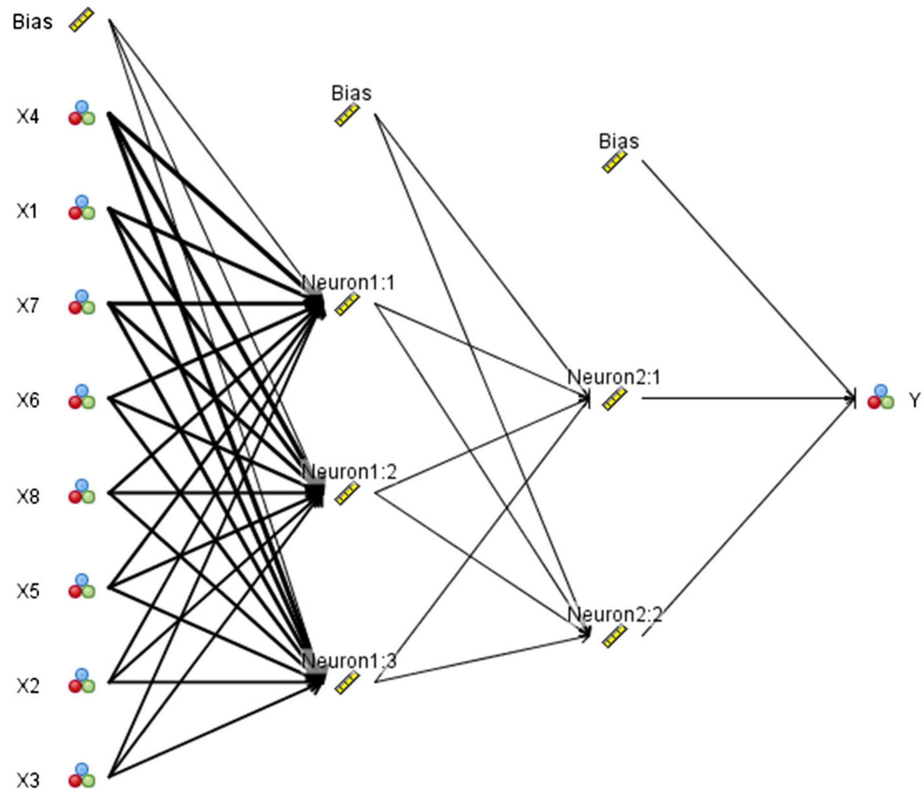
Gains chart Cumulative gains chart is a graphical representation of the advantage of using a predictive model, where the percentage gain is calculated as follows:

$$\text{Gains }(\%) = \left(\frac{Hits\,in\,increment}{Total\ number\ of\ hits}\right) * 100\,\% \qquad (14)$$

The gains chart for the ensemble model is shown in Fig. 14. For example, using the ensemble model, we will gain over 25 % additional correct response at top 40 percentile compared to if we use no model.

Lift chart Lift is a measure of the effectiveness of a predictive model calculated as the ratio between the results obtained with and without the predictive model. The greater the area

Fig. 12 SPSS modeler output for neural network model



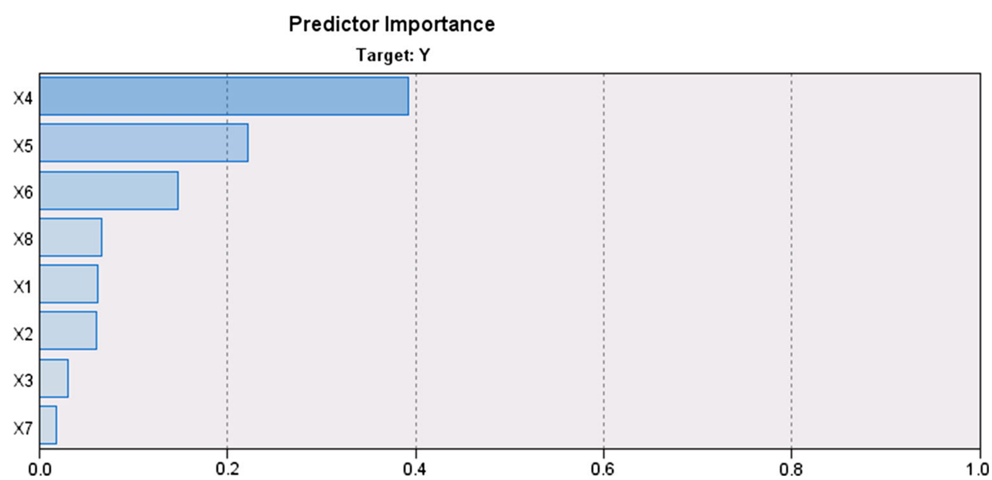


Fig. 13 Predictor importance by neural network model from SPSS modeler

between the lift curve and the baseline, the better the model and the calculation is shown in Eq. (15).

$$\text{Lift Index} = \frac{\text{hits in increment/records in increment}}{\text{total number of hits/total number of records}} \tag{15}$$

The lift chart, shown in Fig. 15, shows how much more likely we are to receive respondents than if we contact a random sample of suppliers. For example, by contacting top 60 percentile based on the predictive model we will reach over 1.7 times as many correct predictions as if we use no model.

ROC curve In a receiver operating characteristic (ROC) curve the true positive rate (Sensitivity) is plotted in function of the false positive rate (1-Specificity) for different cut-off points of a parameter. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. A test with perfect discrim-

Fig. 14 Gains chart

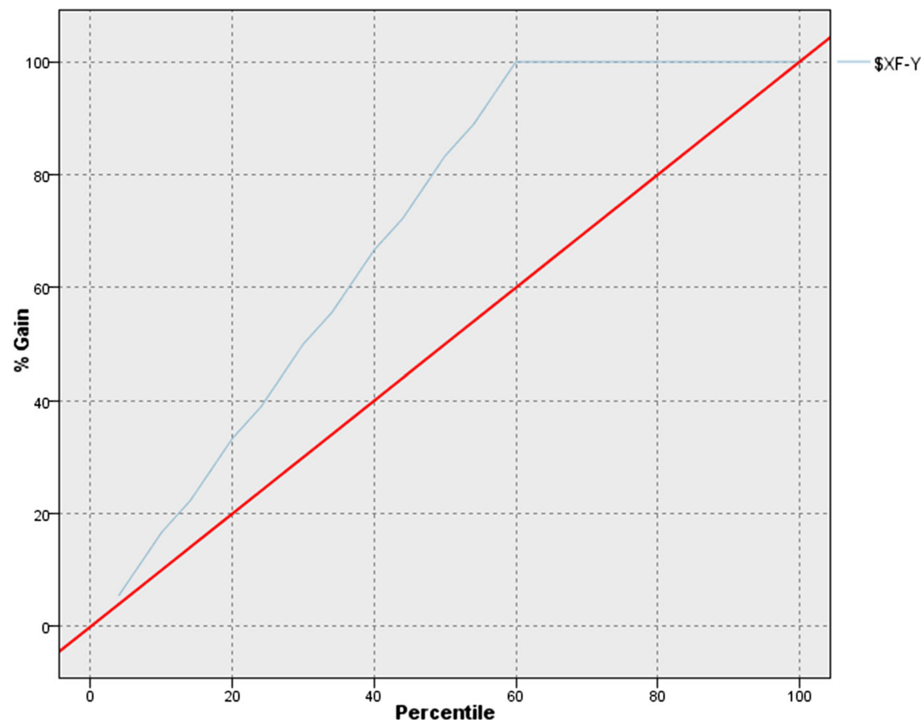
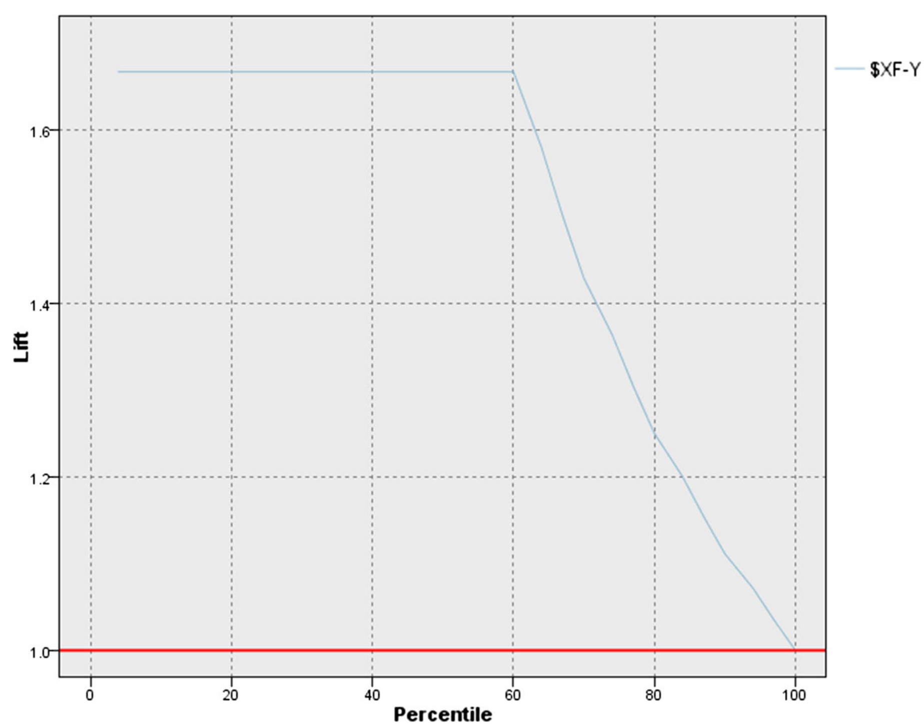


Fig. 15 Lift curve



ination (no overlap in the two distributions) has a ROC curve that passes through the upper left corner (100 % sensitivity, 100 % specificity). Therefore, the closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test. It shows false positive rate (1-specificity) on X-axis, the probability of target =1 when its true value is 0, against true positive rate (sensitivity) on Y-axis, the probability of target = 1 when its true value is 1. Ideally, the curve will climb quickly toward the top-left meaning the model correctly predicted the cases. The diagonal red line is for a random model. The ROC curve is shown in Fig. 16. It shows, using the predictive model, we can about

Fig. 16 Receiver operating characteristic (ROC) curve

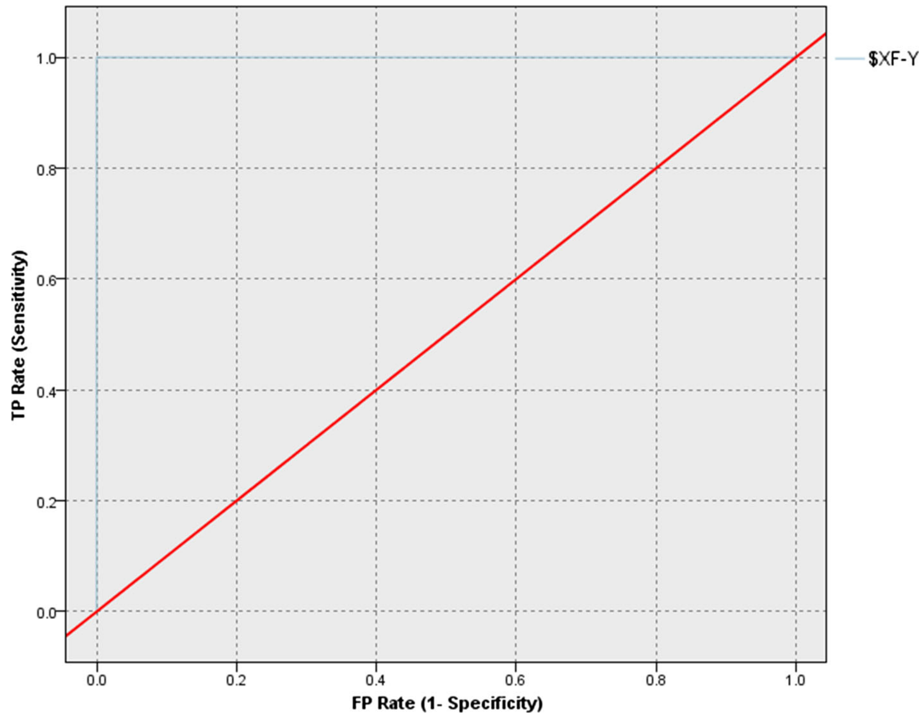


Table 8 Output data

Supplier	X1	X2	X3	X4	X5	X6	X7	X8	Predicted value
Ahmedabad, India	2	3	0	1	1	0	2	2	0.3934
Beijing, China	5	5	1	3	4	1	3	3	0.8791
Daegu, South Korea	2	2	0	2	2	0	1	2	0.2108
Delhi, India	5	2	1	4	4	1	4	5	0.8501
Fujian, China	4	3	1	3	5	1	5	3	0.7721
Guangdong, China	1	2	0	1	3	0	2	2	0.1638
Gujarat, India	4	3	1	5	3	1	5	4	0.7923
Gyeonggi-do, South Korea	1	2	0	1	3	0	2	1	0.1934
Ha Noi, Vietnam	4	2	1	3	4	1	3	4	0.7098
Hanoi city, Vietnam	5	4	1	4	3	1	5	3	0.9056
Ho Chi Minh City, Vietnam	4	5	1	5	5	1	4	5	0.9612
Ho Chi Minh, Vietnam	3	1	0	1	2	0	2	1	0.2903
Hong Kong (1)	5	4	1	5	4	1	3	4	0.9369
Hong Kong (2)	3	2	1	4	5	1	5	5	0.7697
Hunan, China	2	3	0	3	2	0	1	1	0.2332
Jiangsu, China	2	1	0	2	1	0	2	3	0.2012
Jiangxi, China	3	3	1	4	4	0	4	5	0.6695
Maharashtra, India	1	2	0	1	2	0	1	1	0.1169
Seoul, South Korea	2	1	0	3	1	1	3	1	0.2437
Shaanxi, China	3	4	1	4	5	1	2	4	0.6934
Shandong, China	5	5	1	5	3	1	3	4	0.9834
Shanghai, China	5	4	1	4	3	1	3	4	0.8312
Sichuan, China	2	2	0	3	2	1	1	1	0.3604

Table 8 continued

Supplier	X1	X2	X3	X4	X5	X6	X7	X8	Predicted value
Taiwan	5	4	1	3	3	1	3	3	0.6923
Taiwan	4	5	1	2	3	1	4	5	0.8243
Taiwan	4	2	1	5	3	1	3	5	0.7301
Taiwan	1	1	0	1	1	0	2	1	0.1147
Tamil Nadu, India	1	1	0	2	3	0	2	1	0.2904
Tianjin, China	4	5	1	4	4	1	4	4	0.8852
Zhejiang, China	5	3	1	3	5	1	5	5	0.9123

Table 9 Five suppliers with top resilience value and other multi-criteria for AHP

Supplier	Cost	Quality	Resilience	Lead time	Response rate (%)
Shandong, China	1450 ($/ton)	0.82	0.9834	15	62.5
Ho Chi Minh City, Vietnam	1410 ($/ton)	0.88	0.9612	30	54.2
Hong Kong (1)	1390 ($/ton)	0.95	0.9369	25	86.2
Zhejiang, China	1525 ($/ton)	0.87	0.9123	12	52.9
Hanoi city, Vietnam	1384 ($/ton)	0.71	0.9056	18	71.0

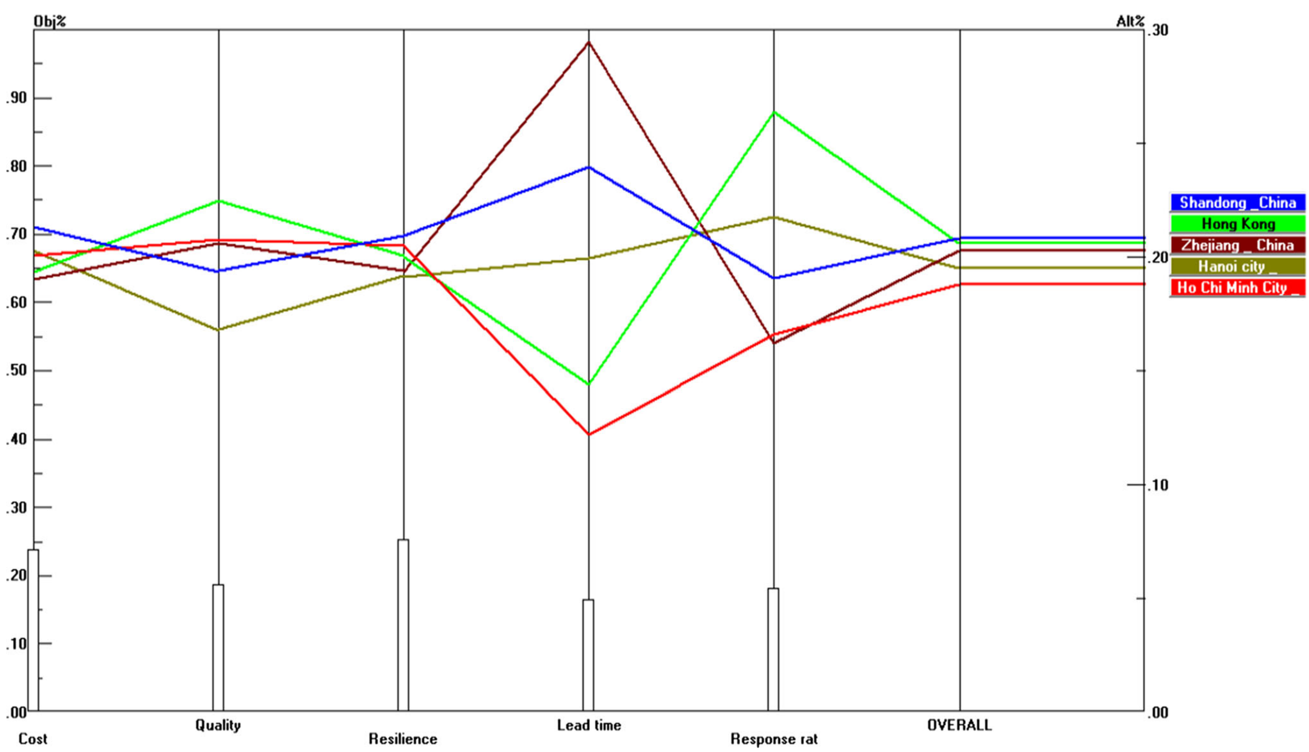


Fig. 17 A performance sensitivity analysis of five suppliers

100 % true positive response and only no false positive response.

Results

The predicted value of the resilience or the probability of individual supplier's resilience using the ensemble model is calculated and represented in Table 8. Among the potential suppliers, top five ones with higher resilience value have been selected for the assessment. The resilience values of these five suppliers along with their values for other criteria are presented in Table 7. Based on Table 9, among the top resilient suppliers, two suppliers are from China, two from Vietnam, and remaining one is from Hong Kong.

Fig. 18 The weights of criteria

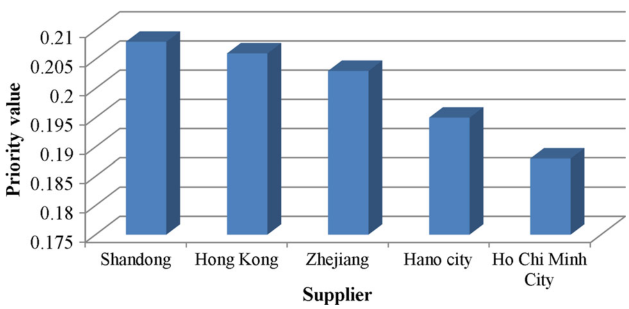


Fig. 19 The priority value for selection of five suppliers

A performance sensitivity analysis has been exerted and the results are illustrated in Fig. 17. As we see from Fig. 17, the supplier located in Shandong (China) has the best performance in overall whilst the supplier located in Hong Kong is the second top one. The performance of individual alternative with respect to each criterion can be compared and analyzed from Fig. 17. The main conclusion is that the performances of suppliers are relatively similar to each other in terms of cost and resilience criteria but significantly different for lead time and response rate criteria. The weights of criteria are graphically represented in Fig. 18. Note that the inconsistency value is a desired value of 0.05.

To analyze the decision for selection of the best supplier, we plot the results of five suppliers obtained from AHP method in Fig. 19. It is clear that the supplier located in Shandong (china) has been contributed the best to the objective (best supplier selection) whilst the Ho Chi Minh City contributed the least. Therefore, the supplier in Shandong is the most preferable one.

Conclusion

In this paper, we first discussed and analyzed the main contributors to the resilience of supplier selection. Resilience supplier selection has been rarely studied in contrast to primary and green supplier selection problem. This paper proposed a hybrid ensemble and AHP approach in which ensemble method is used to calculate the resilience value of potential suppliers based on notion of their absorptive, adaptive, and restorative capacities. Eight contributors to the resilience of suppliers were identified, analyzed, and ranked using ensemble method. We found that robustness, reliability and rerouting are the most important enablers of supplier resilience. Among the potential suppliers, top five suppliers with higher resilience value have been selected. AHP approach has been used to compare those five suppliers when five criteria of quality, resilience, cost, response rate, and lead time are considered.

The findings of this study can be served as a good starting point for assessing impacts of resilience in supply chains. For example, the impacts of resilient suppliers in continuing supply chain operations can be measured and analyzed. The future research efforts can be focused on developing metrics to measure the resilience of suppliers. Those metrics must measure the impacts of supplier's vulnerability on the supply chain continuity. The suppliers' resilience can be measured in terms of vulnerability and recoverability of supplier in the presence of disruptive events. The future supplier selection models may also need to consider the impacts of time to supply failure, dynamic aspect of supply disruption, and also financial loss due to the supply disruption. Fuzzy logic approach can be further used to model the financial loss of supplier due to imprecision associated with intensity and likelihood of disruptive events involve with suppliers.

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