



INTELLIGENT AGENTS AND RISK BASED MODEL FOR SUPPLY CHAIN MANAGEMENT

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Abstract. This paper presents a software agent based framework's architecture for boosting performance in supply chain management applications. The framework is based on agent interaction and semantic web service composition. The purpose of such a platform is to develop flexible business applications for SCM transactions modeling, in collaborative and distributed economic systems. The interaction between agents is limited by a cybernetic model that takes into account several constraints one of the main being bankruptcy risk potential of the peer partner company.

Keywords: risk based model, supply chain, intelligent agents, neural network.

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1. Introduction

Nowadays, the enterprise environment is heavily influenced by the evolution of the IT&C technologies. The main impact of these changes is on the collaborative nature of the economic activity. This results in an increased level of competition at a global scale. Therefore, adapting and efficiently taking advantage of these changes represents a real challenge for the top and medium management. The enterprise steering committee has to permanently be updated with the latest discoveries so that to obtain maximum satisfaction.

In the context of dynamic business, maximizing and optimizing business performance is a critical requirement for profitability. The new economy considers enterprise interoperability along with efficient knowledge management strategies as one of the main prerequisites for improving the level of economic performance.

All the transformations that occur in the enterprise economic environment are closely connected and have a great influence over the globalization trend the economy is heading towards. The global market can be characterized by increased levels of interoperability that reflect into the integration of multiple and different information systems which are able to share, manipulate and combine knowledge so that to facilitate the enterprise collaboration process. Having given all the above facts, we can conclude that the very frequently used term “integrated company” is not of great interest anymore. Presently, it is substituted by collaborative information systems composed of business networks that are linked to independent partners that provide individual services and goods.

The changing economic conditions and the emerging global economy create a context in which companies that quickly and accurately evaluate new market opportunities and create innovative products and services can perform. Fully integrated traditional enterprises are being replaced by business networks in which every company is specialized in certain services or products (Gosain *et al.* 2005), (Nissen, Sengupta 2006).

In the economic systems that are based on enterprise interoperability, the business flow is more complex than in the non-collaborative ones. The business processes that compose the flow have to be designed as to take into account both the internal and the external economic environments. While the internal enterprise environment is composed of: activities such as marketing, production etc., actors (all the persons involved in the activities) and resources that characterize and assure its main functions, the external one consists of actions and behaviors that are part of the collaboration flow and establish the enterprise place and role in the global economic sector in which it performs. The supply chain activity is one of the most representative examples of enterprise collaboration and interaction.

In order to efficiently model and coordinate transactions in such complex economic systems, advanced collaborative software business solutions are required. The distributed nature of the collaborative economic environment can be represented and modeled by using web services and intelligent agents that interact with each other. According to Papazoglou, Kratz (2007) this requires that several web service operations or processes attain transactional properties reflecting business semantics, which are to be treated as a single logical (atomic) unit of work that can be performed as part of a business transaction.

This paper presents a software agent based framework architecture for boosting performance in supply chain management applications. The framework is based on agent interaction and neuronal networks. The purpose of such a platform is to develop flexible business applications for SCM transactions modeling in collaborative and distributed economic systems. The interaction between agents is limited by a cybernetic model that takes into account several constraints one of the main being bankruptcy risk potential of the peer partner company.

The first section of the article consists of a short literature review so that to establish the place of our research in the current international research trends. The following section

describes the economic model that is applied. The last section presents the main elements of the multi-agent supply chain framework and how the economic model is integrated.

The innovative features of our proposal are the flexible agent search, the use of location and semantic annotation and also the use of the economic model that considers bankruptcy risk as one of the variables when evaluating the possible future business partner.

2. Agent and semantic web service technologies applied in business flows

When business processes cross over the boundaries of the organization they become more difficult to model and the software applications that are to be implemented in this situation are very complex. There are some main elements that have to be taken into consideration Papazoglou, Kratz (2007):

- Establish a common interaction language between distributed and distinct systems: unanimously agreed communication and business standards, common trading documents format, etc.
- Business protocols for message exchange that specify: flow of messages representing business activities among trading partners (without requiring any specific implementation mechanism). Collectively, business process protocols and associated data format and message exchange standards provide the means for automated, system-to-system exchange of data and messages between trading partners.

Nowadays, there are true businesses networks composed of independent partners that offer to the others their specific services or products. Therefore, we can assume that companies become product and customer oriented structures. In the context of dynamic business, maximizing and optimizing business performance is a critical requirement for profitability.

Software agents are complex autonomous software entities that behave and interact with each other in order to collaboratively fulfill the purpose of the entire multi-agent system. One important feature of multi-agent systems refers to their ability of decomposing complex problems into more easily manageable sub problems. This feature is particularly useful for representing supply chains as networks composed of autonomous business that negotiate, manufacture and distribute products and services, Bodea, Mogos (2007).

Using multi-agent systems in collaborative supply chain management systems implies modeling communication and cooperation between agents in order to allow demand-supply processes. As shown in Di *et al.* (2009) agents can communicate and interact with each other through ontology language.

The demand for flexible, adaptive multi-agent behavior has increased the challenges inherent in the design of multi-agent systems Bond, Gasser (1988). As a result, the attempt to automate the collaboration process between enterprises has been amplified. The payoff for meeting these amplified challenges is the creation of more capable, more robust multi-agent systems.

In general, adapting the organization of a multi-agent system enables agents to overcome problems or improve performance by changing the pattern of information, control, and communication relationships among agents as well as the distribution of tasks, resources,

and capabilities. For example, agents may be able to overcome agent failure (by restructuring collaborative decision-making to exclude failed agents), communication failure (by allowing agents awaiting orders to eventually take initiative), and under-performance (by allowing agents to establish new collaborations that may work better) Martin, Barber (2006).

Intelligent software agents have been used in enterprise independent software systems integration process, not only to assure an approach for functional integration, but also to facilitate the use of business intelligence and collaboration among enterprises for their communication, interaction, cooperation, pro-activeness, and autonomous intelligent decision making.

In order to achieve the objectives of the current enterprise interoperability trend, we propose a framework that combines web services and software agents so that to provide an efficient service selection, retrieval, composition and integration.

Multi-agent systems are closely connected to web service technology because they represent interoperable, portable and distributed solutions. Agents and web services may be related in different ways: agents use web services, web services are in fact agents or agents are composed of, deployed as, and dynamically extended by web services Martin *et al.* (2005).

3. Supply chain management platform based on agents' interaction

This paper illustrates an agent based software platform for modeling supply chain management application in the modern collaborative, knowledge based economic environment. Agents' behavior simulates human interaction, communication and negotiation processes.

The proposed framework enables the implementation of multi-agent supply chain systems that allow customers to easily identify suppliers that meet their business needs. All participants in the supply chain are modeled using software agents.

Similar to the real world business they represent on the internet, each agent has inputs and outputs. Outputs represent the services and products the agent offers, their price levels and technical features. Inputs consist in raw material, required-services or sub-assemblies needed in order to manufacture a specific output product or in order to provide a specific service.

In order to choose the best supplier for each input a series of features have to be taken into account. These features are combined in an evaluation function that is used to compute a score for each potential business supplier. Every agent will have its own evaluation function for selecting the most suitable business partners. The function is parameterized, so that each agent can choose different importance weights for the constraints according to its preferences.

In our paper, before applying the selection function we perform a classification of the companies based on their risk of bankruptcy. For the selection function we consider as variables: distance, price, technical features. This parameters can change based on the purpose of each business application. In this manner we assure an increased level of flexibility to our solution. In order to evaluate and predict the bankruptcy risk, we developed a wavelet neuronal network based model.

3.1. Bankruptcy Prediction Model

In order to classify the identified suppliers into secure and non-secure ones we developed a binary classification model that is based on wavelet neuronal networks. Due to the competitive exchange economy, each firm can be seen as a producer or consumer looking to maximize either its profit or utility Rezvani, Analoui (2010). The algorithm has several stages that will be presented in detail below.

Stage 1: Prerequisite phase – data collection

This stage consists in creating a training set for the next phases of the algorithm. The set consists of forty five companies that are grouped into profitable, (thirty two companies) and less profitable ones (thirteen). We used the “profitable companies” term as a general term, these companies being characterized by sustainable growth and “proficient” economic strategy demonstrated by the values of certain indicators. For this we consider ten indicators that will be analyzed and in the variable selection phase will be selected only the ones that qualify to be part of the binary classification model. The computations are developed in **MATLAB 7.9.0** and we took into account several data sources such as: BVB (2011), ANAF (2011), Mfin (2011), ListaFirme (2011), KTD (2011).

Stage 2: Data mining and variables selection stage

The data mining process consists of identifying a list of financial indicators that can be used to predict bankruptcy. Furthermore, over this stage we compute the values for indicators. Predictive variables selection is made in three steps:

Step 1: The bankruptcy prediction literature was reviewed and a number of 50 variables were selected, these variables representing the characteristics of profitability, liquidity, activity, stability, growth, trend, liability, structure, etc., see Table 1.

Table 1. Indicators used in financial distress Delcea (2010), Delcea, Scarlat (2010)

Category	Indicator
Profitability	Gross income to sales
	Earnings before interest and tax to total assets
	Return on total asset
	Financial expenses to liabilities
	Cost of sales * Cost of sales growth ratio
	Net income to total interest
	Profit margin
	Cost of sales to net sales
	Financial expenses and normal profit to total assets
	Financial expenses growth rate to assets
	Non-operatory expenses growth rate to assets
	Net profit to equity

End of Table 1

Category	Indicator
Activity	Payables turnover
	Inventory growth rate to sales
	Current assets turnover
	Fixed assets turnover
	Inventory turnover
	Total assets turnover
	Total assets turnover * sales growth rate
Liquidity	Solvency ratio
	Window coefficient
	Cash flow to total liabilities
Stability	Debt ratio
	Long term debt ratio
	Quick ratio
	Net worth to total assets
	Cash and cash equivalents to current liabilities
Growth	Growth rate of primary business
	Growth rate of total assets
	Growth rate of sales
	Total asset change ratio
	Total asset growth rate
	Interest increase ratio
	Subsistence income to total assets
Trend	Financial expenses growth
Structure ratios	The proportion of fixed assets
	The proportion of current assets
	The proportion of equity to fixed assets
	The proportion of current liability
Liability	Current ratio
	Asset liability ratio
	Ratio of cash to current liability
	Equity to debt ratio
	Ratio of liability to tangible net asset
	Interest coverage ratio
	Ratio of liability to market value of equity

Step 2: Among them, eight variables were retained based on their availability on finding online necessary data;

In order to obtain the necessary data from the Internet, a web crawling application was developed. The application takes as input the CUI (fiscal code) and crawls the sites that were presented above. The web crawler module not only looks for data over the Internet, but also computes the financial indicators within the identified set based on the available data. For the training data set composed of 45 companies the application was able to identify data only for 10 indicators which will be presented in detail. Figure 1 presents a print screen from the web crawling application based on a single company search.

If no Fiscal code is entered the application crawls for the companies that we considered as a training data set. The results are displayed in Figure 2.

The following eight variables are the ones that manifested the great availability in finding their values through web crawling:

- X1 – Debt ratio (DR);
- X2 – Quick assets to total assets (QA2TA);
- X3 – Return on equity (ROE);

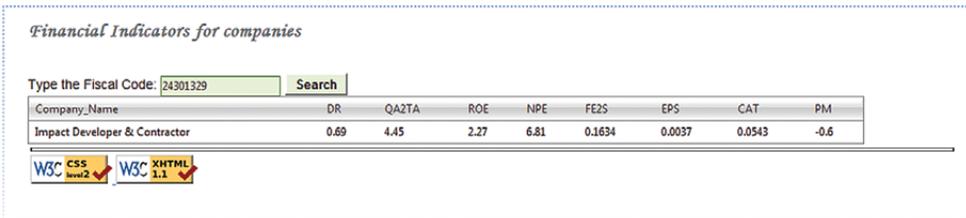


Fig. 1. Web crawler print screen displaying the results for a specific search

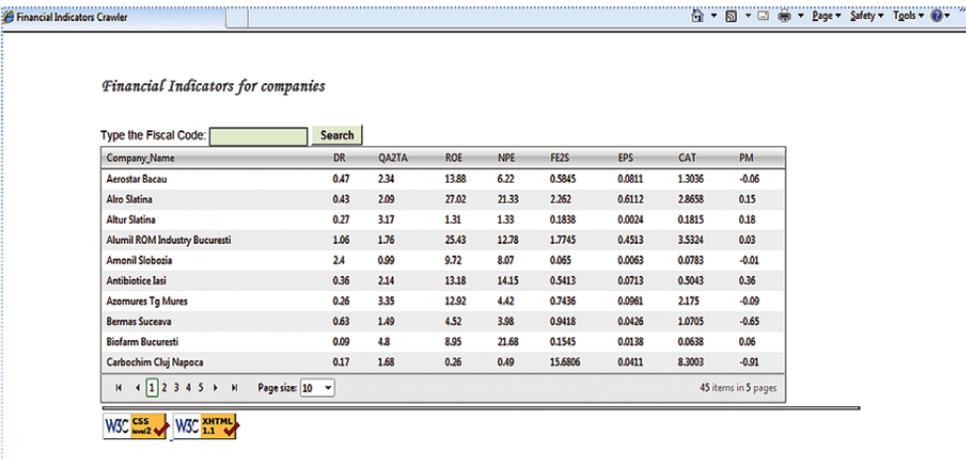


Fig. 2. Web crawl screenshot when no fiscal code is entered

- X4 – Net profit to equity (NPE);
- X5 – Financial expenses to sales (FE2S);
- X6 – Earnings per share (EPS);
- X7 – Current assets turnover (CAT);
- X8 – Profit margin (PM).

Step 3: Using feature selection on standardized data for a specific significance level, a number of three variables are retained and used in the proposed model.

As Guyon, Elisseeff (2003) have identified the potential benefits of feature selection:

- facilitating data visualization and data understanding;
- reducing the measurement and storage requirements;
- reducing training and utilization times;
- defying the curse of dimensionality to improve prediction performance.

The feature selection algorithm is suited for training wavelet neuronal networks. In order to determine the most important features, we train a sample neural network using all the eight features presented at the previous step as shown in Figure 3. The network consists of three layers: input layer, hidden layer and output layer. All the nodes in each layer are fully connected to the nodes in the next layer. The input layer has 8 nodes corresponding to the features taken into consideration. The hidden layer has m nodes and the output layer contains only one node, representing the classification. The network is trained using the considered firms in order to determine the weights between the nodes. We consider w_{ij} the weight of a connection between the input node i and the hidden node j ($i = 1...n_p; j = 1...n_h$) and w'_j the weight of the connection between the hidden node j and the output node. In our case the number of input nodes, n_p equals 8, the number of variables taken into consideration.

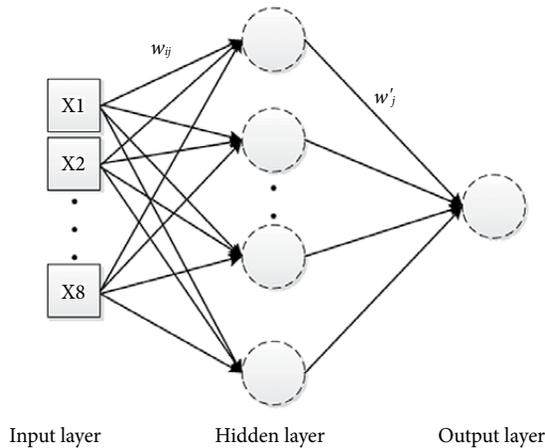


Fig. 3. Choosing the most important features based on their influence on the neural network output

The most important features are the one for which the input has the highest absolute influence on the output. We can calculate the impact of the input node i on the output of the hidden node j using the following formula in which we divide the weight of the hidden to output link with the relevance of the i to j connection over all the inputs to hidden node j :

$$w^{*ij} = \frac{|w_{ij}|}{\sum_{i=1}^{n_p} |w_{ij}|} * |w'_j|. \quad (1)$$

For each input node we compute the importance indicator:

$$h_i = \frac{\sum_{j=1}^{n_h} w^{*ij}}{\sum_i \left(\sum_{j=1}^{n_h} w^{*ij} \right)} * 100 \quad (2)$$

(1) and (2) can be combined in a single equation:

$$h_i = \frac{\sum_{j=1}^{n_h} \frac{|w_{ij}|}{\sum_{i=1}^{n_p} |w_{ij}|} * |w'_j|}{\sum_i \left(\sum_{j=1}^{n_h} \frac{|w_{ij}|}{\sum_{i=1}^{n_p} |w_{ij}|} * |w'_j| \right)} * 100. \quad (3)$$

Based on the importance indicator, the following three variables were selected:

- X1 - Debt ratio; (stability);
- X7 - Current assets turnover; (activity);
- X8 - Profit margin; (profitability).

Debt ratio calculated as:

$$DR = \frac{TL}{TA}, \quad (4)$$

where: TL = Total liabilities; TA = Total assets.

DR indicates what proportion of debt a company has relatively to its assets. It is categorized into the solvency and stability ratios category. Solvency may reveal the some firms' failure causes rooted in its financing policy. This ratio also gives an idea over company's potential risks in terms of debt load and has a negative relation with bankruptcy occurrence.

Current assets turnover (CAT) ratio determined by dividing the sales to the current assets is an efficiency ratio. A higher efficiency can be translated through higher profitability and better liquidity and finally to lower default risk. Etemadi *et al.* (2009)

$$CAT = \frac{TS}{CA}, \quad (5)$$

where: TS = Totals sales; CA = Current assets.

Profit margin (PM) calculated as net profits divided by sales or as net income divided by revenues. A higher level of this ratio means better coverage production costs and a lower default risk.

$$PM = \frac{NP}{TS}, \tag{6}$$

where: *NP* = Net profit; *TS* = Total sales.

For the both considered categories (profitable and less profitable) and based on the initial data sample (forty five companies), the mean values of the X1, X7 and X8 indicators are calculated and their values could be found in Table 2. These are going to be used in the next step, which deals with the binary classification of new firms.

Table 2. Means of the variables calculated for the two groups considered in the model

Variable	X1	X7	X8
Means of profitable firms	0.6745	1.4403	0.2428
Means of less profitable firms	0.7946	1.0955	0.0140

Graphically, the mean values of the classification variables for each of the two representative sets are drawn in Figure 4.

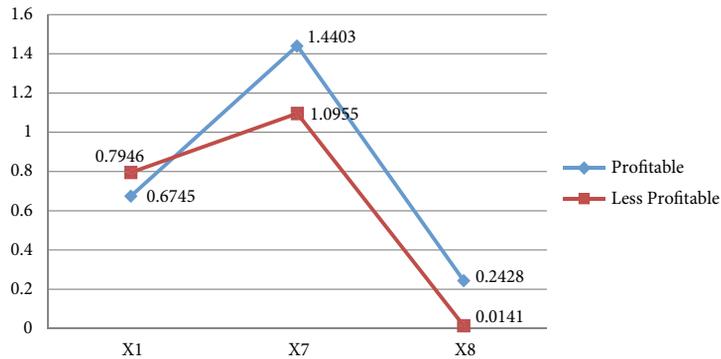


Fig. 4. Mean values representation

In the variable selection phase we have identified a set of three variables that are best representing the situation in which a company can be found. Using the identified variables, we can pass to the next step: using a wavelet network classification model for predicting the future stage in which a firm could be found: profitable or less profitable.

Stage 3: Wavelet neural network classification model

Many approaches currently exist for predicting the corporate financial distress, usually based on discriminant analysis using linear functions. Such approaches have the disadvantage that the patterns need to be linearly separable and the samples must follow a multivariate normal distribution. Other approaches involve binary classification models Min, Jeong (2009) that

involve the calculation of a similarity degree between a newly considered firm and the two considered sets in which a firm could be found. Neural networks emerged as a successful way to overcome such limitations Chauhan *et al.* (2009). They are built from many interconnected processing elements called neurons. The weights associated with the connections between the neurons model the input-output characteristics. Neural networks are used in Cimpoeru (2011) for credit risk assessment. Wavelet neural networks emerged as an approach that does not depend on the set of initial conditions used when defining the neural network structure. Figure 5 presents a representation of a wavelet function using Wolfram Mathematica.

An individual wavelet function is defined by the following formula:

$$\Psi^{a,b}(x) = \frac{1}{\sqrt{|\sigma|}} * \Psi\left(\frac{x-b}{a}\right). \tag{7}$$

Several methods to train wavelet neural networks – WNN exist including Differential evolution and Threshold accepting trained WNN Chauhan *et al.* (2009). A back propagation approach for training a normal neural network is presented in Ruxanda (2010).

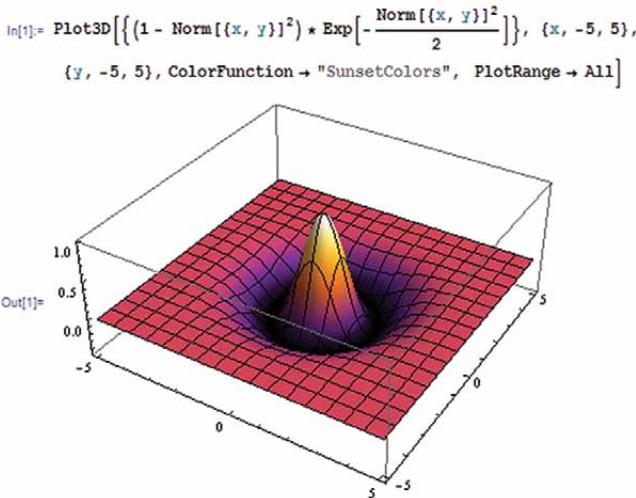


Fig. 5. Wavelet function represented using Mathematica

In order to train the network we use the following steps:

Step 1: We first assign random values for the connections between the input nodes and the hidden nodes and between the hidden nodes and the output node, $w_{ij} \in (0,1)$; $w'_j \in (0,1)$.

Step 2: The output of a sample V_k , $k = 1, \dots, np$, where np is the number of samples, is calculated with the following formula:

$$V_k = \sum_{j=1}^{nhn} w'_j * f\left(\frac{\sum_{i=1}^{nin} w_{ij} * x_{ki} - b_j}{a_j}\right), \tag{8}$$

where: $k = 1, \dots, np$; nin = number of input nodes and nhn = number of hidden nodes.

Step 3: Reduce the error of prediction based on the training data set by adjusting the weights w_{ij} , w'_j , and the values for a , b . The error is computed as follows:

$$E = \sqrt{\sum_{k=1}^{np} \frac{(V_k - \hat{V}_k)^2}{V_k}} \tag{9}$$

Step 4: Return to Step 2 until the error E is as small as possible and the training phase can be considered completed.

The resulting WNN will have three input nodes corresponding to the selected values X1, X7 and X8 as shown in Figure 6.

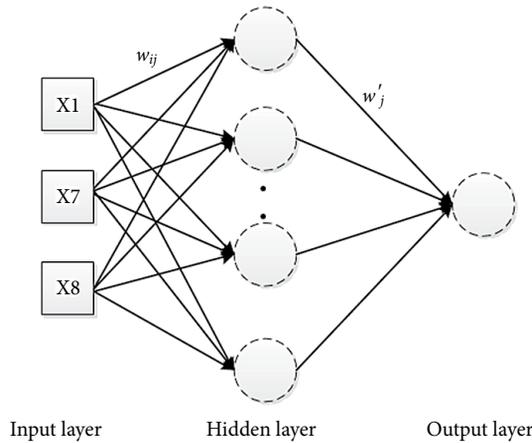


Fig. 6. Bankruptcy prediction model

The stages of the bankruptcy prediction and classification algorithm presented above are summarized in Figure 7.

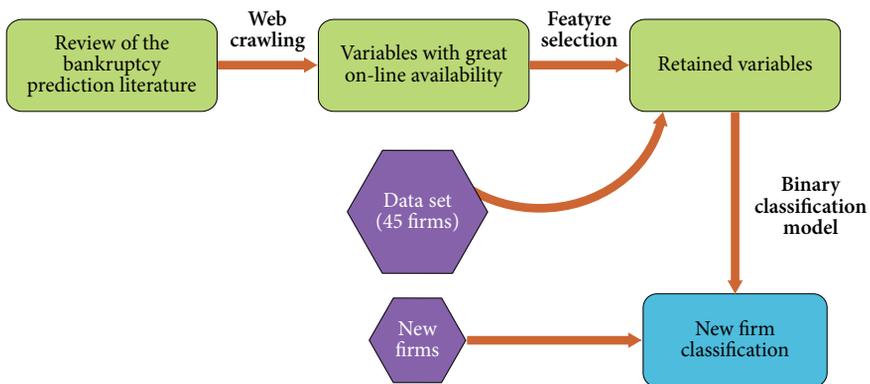


Fig. 7. Bankruptcy prediction and classification algorithm

3.2. Trading agents interaction process

For example, consider, a manufacturer that develops Web service based solutions to automate the order and delivery business functions with its suppliers as part of a business transaction. The transaction between the manufacturer and its suppliers may only be considered as successful once all products are delivered to their final destination, which could be days or even weeks after the placement of the order, and payment has ensued.

According to Fox *et al.* (2000) a supply chain usually consists of suppliers, factories, warehouses, distribution centers, and retailers through which raw materials are acquired, transformed, and delivered to customers.

Although creating specialized agents for these categories implies several benefits we consider that this approach limits flexibility and the overall capacity of the system to model the real business entities. Taking into account that a participant in a supply chain might belong to several of the above mentioned categories and offer multiple services and products we have chosen to implement generic trading agents. Intelligent agents are used in Xiaolong *et al.* (2010) for trading in the construction projects field.

When evaluating offers, agents will first classify the providers based on their profitability by using the algorithm presented above. If a certain supplier is considered safe, the following function is used to evaluate the best offer Cotfas *et al.* (2010).

$$bestOffer = \max_{i=1..m} \frac{\sum_{j=1}^n p_{lj} * \frac{M_{lj}(\alpha_{jk})}{\max_{k=1..o_j} M_{lj}(\alpha_{jk})}}{\sum_{j=1}^n p_{lj}}, \quad (10)$$

where: m = number of suppliers; n = number of technical features; o_j = number of possible values for the feature j ; p_{lj} = importance of feature j for trading agent l ; α_{jk} = possible values of the technical feature j . $M_{lj} : \{\alpha_{jk}; j = 1..n, k = 1..o_j\} \rightarrow \{1..10\}$ = function evaluating the optimality of characteristic j for trading agent l .

If one mandatory rule is not met, the offer is rejected and will no longer be taken into consideration during the evaluation process. Based on previous experience or user input, each agent maintains a list of trusted and mistrusted agents. Importance for the above mentioned parameters can be defined using the dedicated Supplier's Web Interface.

All agents can and usually perform several roles in the supply chain. In Figure 8 the agent called Trader 1 is a supplier for the agent Customer from whom it receives a service or a product request. If Trader 1 cannot complete the request by itself he can request additional services or subassemblies to other agents becoming thus a customer. Trader 2, 3 and 4 are possible suppliers for Trader 1, but they also can become customers for other agents. If a trader agent cannot supply the requested service or product in the requested conditions, it returns a void offer.

Ontology Web Language (OWL) was used to semantically describe the products and services and also their technical characteristics. All configurations are done using the trader agents' web interface.

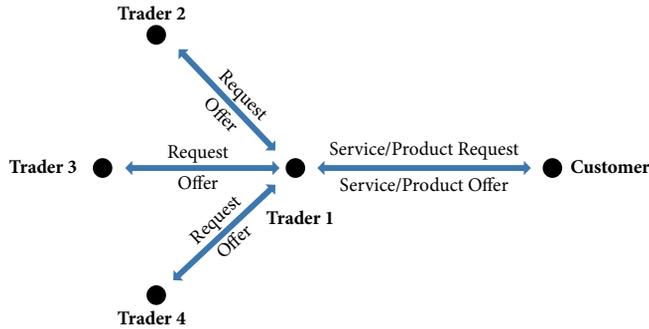


Fig. 8. Agent trading

Although location is considered an important aspect, many existing frameworks fail to use it at the full potential or omit it completely. We consider location import as it might have a big influence on transport costs and risks involved. It also helps us narrow the search when the requested service or product can be delivered only in certain areas. GPS coordinates are stored for all agents involved. Besides, for agents offering distribution services, GPS coordinates for the delivery areas are also stored as geographic shapes (polygon) using Geographic Markup Language (GML) standard format as defined by Open Geospatial Consortium (OGC). Using a standard format will allow us to integrate the framework with other applications like the one described in Dumitrescu *et al.* (2010).

3.3. Identifying the best offer by using intelligent agent interaction

The communication between agents is based on OWL ACL messages compliant with FIPA standards. The steps that are taken into account are presented below Chauhan *et al.* (2009).

Step 1: All Domain Directory Facilitator (DDF) agents register themselves with the main Directory Facilitator (DF) agent. Domain Directory Facilitator agents will keep information about service from a certain domain. A trader agent first queries the DF agent in order to obtain the available DDFs and then, it registers its services and products with the corresponding ones.

As shown in Figure 9, the framework is implemented in a distributed manner that allows having multiple DF agents running on different machines. Communication between the distributed components is implemented using web services for better interoperability across heterogeneous computing environments. The Web Service Agent (WSA) agent manages the translation between ACL messages and web service calls and constantly maintains a list of DF agents on other machines.

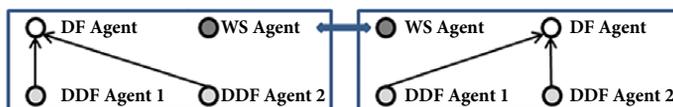


Fig. 9. Distributed agent-based architecture

Step 2: As the supply chain is a customer demand-driven system, the flow starts from the customer's incoming orders. The customer agent first queries the DF and DDF agents on all machines for the list of supplier agents that provide a certain service or product.

Step 3: The customer agent sends its demand to the seller agents discovered in the previous step. The demand specifies the requested delivery addresses using GPS coordinates, the requested products, their technical features, quantity and maximum delivery date.

Step 4: Each contacted supplier agent analyzes the customer's demand and responds in case of match. First it compares the geographic position of the customer with its points of sales covered surface. Next, the seller agent compares the request products or services with his own data described using OWL. Using OWL proved to be a good solution to overcome data heterogeneity. Inference was implemented using Jena to better understand the customer's request. If the seller agent can't provide the requested service or product by itself (ex: it needs to buy subassemblies or raw materials), it will need to find suppliers. Thus, the seller agent becomes a customer for other seller agents and the process repeats starting with Step 2 (Figure 8).

Step 5: The customer agent continues to communicate and negotiate with the agents that positively respond. The offer evaluation takes into consideration both mandatory rules and the evaluation function (bestOffer). More than one seller agent might be selected if necessary in order to meet the required quantity. If the customer agent is not the initial customer, but a seller agent searching for necessary sub-assemblies or services, the algorithm continues with the selection of the best seller offer in the previous recursion step. The algorithm ends when the best seller offer evaluation is done by the initial customer agent.

As shown above, the algorithm is implemented in a recursive manner that allows each seller agent to become a customer agent if needed. This approach guarantees a high degree of flexibility in generating the supply chain. The customer agents can take into consideration a set of predefined rules when selecting suppliers like shown in Figure 10.

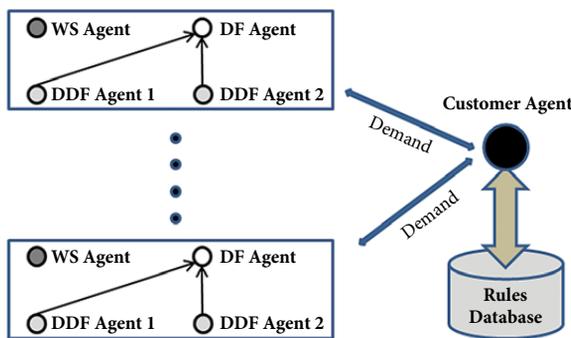


Fig. 10. Agent search in supply chains

Additional reasoning capabilities can be added to seller agent in order to enable the seller agents to adapt prices according to market situation so it can maximize its revenues by selling at appropriate prices.

4. Conclusions

This paper presents an agent based framework that can be used for modeling Supply Chain Management application in the process of identifying the most convenient suppliers. The framework has an evaluation function for the best offer that is very customizable in the sense of enabling business application developers to take into account various types of constraints. Furthermore, this software solution also incorporates a bankruptcy prediction module based on neuronal networks that pre-classify potential suppliers based on their risk of going bankrupt, thus reducing the dimensions of the search space.

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