THE *E-NEGOTIATION* AS A TOOL FOR LOGISTICS OPTIMIZATION IN AN INDUSTRIAL DISTRICT

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ABSTRACT

The aim of this work is to find an optimal solution to operational planning of freight transportation in an industrial district. More specifically, we propose an architecture that drives agents, that is firms in the industrial district, to negotiate in logistics field to minimize the total transportation and environmental costs. The idea is to achieve logistics optimization setting up a community made of district enterprises. We address the situation in which a centralized coordinator helps the agents to reach an agreement, while preserving a satisfactory level of system efficiency and fairness. The implemented algorithm uses the fuzzy aggregation criteria to improve the logistics system performance. The objectives are: maximizing customer's satisfaction, and minimizing the number of trucks needed. A fuzzy clustering algorithm (FCM) and a Fuzzy Inference System (FIS) are thus proposed to achieve these objectives. The proposed framework can be used to provide real time solutions to complex practical logistics and negative environmental impacts.

Keywords: industrial districts logistic, inter-firms relationship, fuzzy multi-agent systems, negotiation.

INTRODUCTION

Pyke and Sengenberger (1992) describe the main characteristics of an Industrial District as "the existence of strong networks of (chiefly) small firms". This "togetherness" implies a cultural homogeneity that gives rise to an atmosphere of cooperative and trusting behaviour in which economic action is regulated by implicit and explicit rules. Marshall (1925), the author of the original concept of the Industrial District, identified also a class of external economies (benefits) obtained by individual firms from the increased pooling of common factors that include skilled human resources, specialized suppliers and technological spillovers. Different models have been proposed to investigate the inter-firm relationships in Industrial Districts, such as the constellations of firms, the flexible specialisation model, the milieux innovateurs, the firm networks, and the clusters. Each model emphasises different and complementary aspects of Industrial Districts, yet all of them focus on the features of inter-firm relationships (Carbonara, et al. - 2002). Those models show that the cooperation among Industrial District firms could represent a way to improve their competitiveness. According to this, we assert in this paper, that Districts Firms should operate in a cooperative way, in order to optimize logistics performance.

Today, logistic chain has been playing an increasing role in industrial system. The key issue to its optimization is to deliver the goods on time, in order to assure customer satisfaction and, at the same time, to minimize the costs. Many efforts have been endeavouring to improve the logistic performance to achieve high agility without increasing costs.

For the logistic system, the optimization problem is a *multi-objective problem*. In fact, we take into account conflicting variables to be optimized like, for example, the difference between proposed and desired delivery dates, and the number of trucks used. Although an optimal combination of criteria is highly desirable, this combination is very difficult in practice. With the increase of agents' expectations in terms of low costs and high quality of services, the logistic planning projects are involving trade - offs among different incompatible goals.

This research proposes a method to combine those criteria through a negotiation system, using the Fuzzy Logic. The work focuses on optimization of freight transportation demand expressed by firms in an Industrial District. The aim is to find an optimal solution, or rather the nearest one to the optimum, in solving logistic problems. The paper also offers evidence that firms working in a cooperative way show a higher performance.

The paper is organized into the following sections: introduction; a description of the logistic problem within Industrial district firms; the proposed method; finally, conclusions.

LOGISTICS PROBLEMS AND NEGOTIATION ISSUES IN INDUSTRIAL DISTRICTS

Problem description

Industrial Districts are territorial agglomerations of small-medium firms located into a specific geographic area, and integrated through a complex network of inter-firms relationships. According to Carbonara et al. (2002), Industrial Districts have three different evolution stages: Formation, Development and Maturity. During the first stage, the dimension of an Industrial District is set up as the local area, characterised by craftsman-like firms, in which two main processes can take place: (1) decentralisation of production, carried out by large firms internal or external to the area, or (2) agglomeration of a craftsman-like entrepreneurial system within that area. In Industrial Districts, potential competitive advantages can be increased as much as the network is efficiently organized. However, frequently in Industrial Districts there is a lack of inter-firm relationships: companies ignore each other, so they behave like individual agents. Therefore, "coordination", "interaction", and "negotiation" could represent, especially among industrial districts firms, a chance to solve logistics optimization problems.

Nowadays, logistics management is getting more and more a competitive factor among industrial firms, since it produces value for customers by improving services and lowering costs. Small firms – usually forming Industrial Districts - could deal with more problems than big companies in logistics. Commonly, small firms contact one by one transportation services providers, just when they need to deliver their products. In other words, small and medium firms in an industrial district generally require "on demand" transportation services. However, vehicles used for transportation are frequently not filled up, since production of a single company could be not enough to fill a truck. As a consequence, transportation costs and external diseconomies such as accidents, pollution and traffic congestion increase.

The negotiation in logistics as a solution

In the context of district logistics, interaction is one of the most important features at agents' disposal to share information, perform tasks, and achieve their goals. In a multi-agent system, negotiation is a key form of interaction that allows a group of agents to reach mutual agreement regarding their beliefs, goals, or plans. Negotiation is a tool through which participants arrive at a specific agreement under conditions of strategic interaction or interdependent decision making. However, it has been for long recognized as a time-consuming process, since all parties involved try to pursue their own interests in the face of conflicting goals. Furthermore, even in the simplest negotiation, individuals frequently reach only sub-optimal (or so-called Pareto-inferior) agreements.

Applications of negotiation are mainly in logistic management, telecommunication network management, and electronic trading system, which require virtual entities, representing different stakeholders, to interact in a flexible manner.

In these applications, conflits often arise because agents represent distinct stakeholders with different perspectives and different preferences. In fact, agents act autonomously and, for example, decide by themselves what actions they should take, at what time, and under what terms and conditions. Automating negotiations also opens up a number of new possibilities. With respect to its face-to-face counterpart, the potential advantages of automated negotiation are:

1. Face-to-face negotiation is time consuming and hence expensive. Instead, by automating the process, negotiations can take place much more frequently, between many more partners, for goods of much smaller value.

2. Face-to-face negotiation is often considered either too embarrassing or frustrating. Moreover, automated negotiation system can help agents facing problems often too difficult to handle.

3. Automated negotiations do not require the participants to be collocated in space or time. This means that the number of entities with which an agent can negotiate is increased.

4. Automated negotiations allow to minimise the amount of private information shared. Agents communicate only when necessary since the information is exchanged only during negotiation.

Because a physical multi-agent system operates on the Internet, industrial district firms could cooperate in a more open and dynamic environment than the traditional one. Internet enables a shift from individual business processes toward a more distributed, collaborative business model.
In this paper we proposed a multi – agent, e-negotiation system where, in order to optimize logistics performance, Industrial District firms operate in a cooperative way. Internet and web services are thus used to connect logistic agents.

THE PROPOSED ARCHITECTURE OF NEGOTIATION

In a decision-making practice, individual preferences are often expressed through linguistic terms, which reflect imprecise values. Thus, precise mathematical models are not able to tackle such situations. To deal with the imprecision of decision makers' preferences, a fuzzy approach has been proposed. A relatively practical introduction of fuzzy set theory into conventional decision-making models was presented by Zimmermann (1987). Following this, further research was carried out in the decision-making area. In particular, some results in fuzzy group decision-making have been reported in the last few years. Nishizaki and Seo (1994) proposed an interactive fuzzy trade-off evaluation method in group decision-making. Lee (1996) presented a method for group decision-making using fuzzy set theory for evaluating the rate of aggregative risk in software development. Hsu and Chen (1996) implemented a similarity aggregation method for aggregating individual fuzzy opinions into a group of fuzzy consensus. Kacprzyk et al. (1992) used a fuzzy majority concept to aggregate group members' preferences and create a decision. More recently, approaches for aggregating fuzzy opinions in multiple criteria decision-making, and the group decision-making environment, were investigated.
In general, group decision-making has been studied from many perspectives including psychology, sociology, political science, economics, applied mathematics, engineering, computer science and artificial intelligence (Bose et al., 1997; Rao and Turoff, 2000; Lai, 2002; Shim et al. 2002; Vogel et al. 2001). A dimension adding difficulty and complexity in studying and handling group decision-making is the fact that group decision-making involves all these member properties: individual preferences on solutions, individual judgments on solution selection criteria, individual importance (weight) in attempting to reach an optimal solution. Each of these aspects has been studied on an individual basis, resulting in an extensive literature on the subject (Eom, 1998; Sakawa et al., 1987; Zhang and Lu, 2002).

The framework

Organizations frequently require decisions to be made by a cooperative group. A decision may involve optimization of multiple conflicting objectives that should be considered simultaneously. The final decision is then selected from a set of "good" alternative solutions

using a set of selection criteria (rules). Consequently, the aim in making group decisions with multiple objectives is to obtain a satisfactory solution that is the most acceptable for the group of individuals as a whole over the set of optimal solutions (Bui, 1989; Korhonen and Wallenius, 1990; Lu and Quaddus, 2001).
The decision-making procedure has to be performed through many negotiations among a group of decision makers. Therefore, determining the 'best' satisfactory solution in a group requires the aggregation of individual roles and preferences. In real environments, group decision-making has to face various conditions (Karacapilidis and Gordon 1995).
Our proposed system takes to account conflicts and aggregation situations among group members. Conflicts of interest are inevitable, and support for achieving consensus and a compromise is required. The proposed framework integrates these properties:

5. decision makers may have different contractual power and availability to negotiate;

6. decision makers express fuzzy preferences for alternative solutions;

7. decision makers are willing to cooperate and to share information;

8. decision makers can give different judgments on concession during negotiation.

The final group decision will be made through aggregating preferences of group members on alternative solutions taking into account their weights and judgments on selection criteria. The final decision is expected to be the most acceptable by the group of individuals as a whole (fig.1).

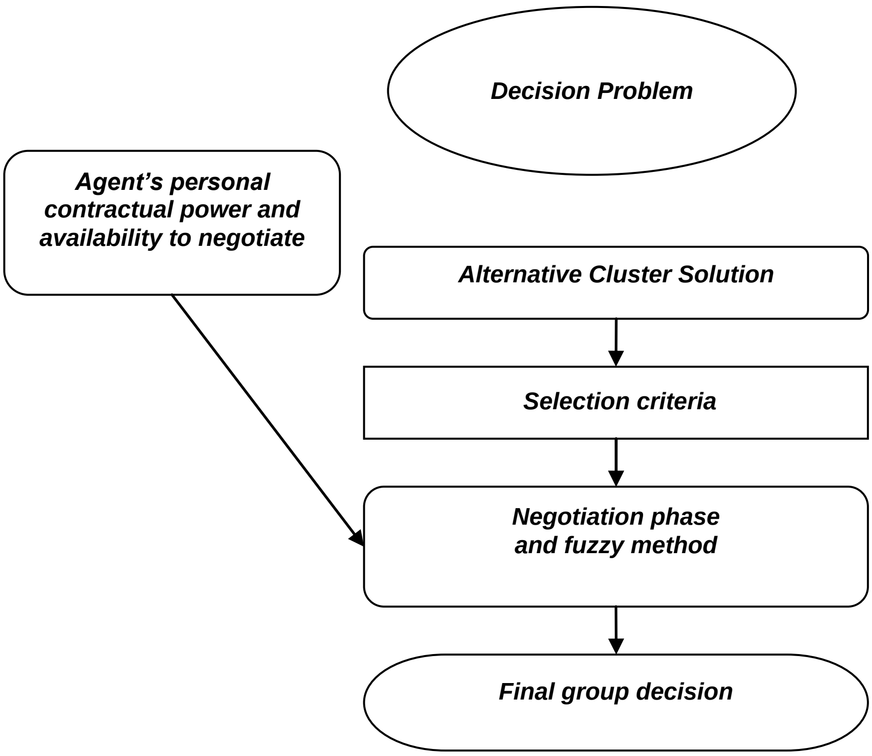

Figure. 1 - The group decision framework

In this paper, we propose the creation of a network among logistics services customers, in the following called "agents". The proposed network allows a set of agents improving logistics through information exchange and negotiation, and reaching a mutual agreement about goals or plans. We argue that if information is available to all parties, the negotiation will be more efficient. Based on the assumption that the parties are willing to do so, this paper proposes an approach for automated negotiation based on concessions. However, this approach requires all parties to surrender part of their privacy (i.e., to reveal their shipment demand attributes). Since they are basically unwilling to disclose private information during a negotiation (Heiskanen, Ehtamo, Hämäläinen 2001), the system minimizes the amount of information that agents reveal about their preferences. In the presented framework, agents are aware of the existence of other similar agents. However they do not have an explicit view of the information about the shipment demand of other agents. The information match is done by the Virtual coordinator, as explained in the following section. In this way, it can argue and attempts to persuade explicitly an agent to change, for example the date to deliver. Only when the negotiation phase is ending, agents exchange information among themselves.
In this paper we have considered vertical and horizontal relationships power in supply chain. Although generally logistics cooperation and contractual power (fig. 1) often have a vertical perspective (e.g., buyer-supplier), horizontal cooperation is considered an interesting approach to decrease costs, improve service, or protect market positions among others. This, despite the competitive element in horizontal cooperation increases the threat of opportunism, and lowers the level of trust because one participant may use information gathered in the cooperation to improve its market position at the expense of other participants (Dullaert, Fleuren, Cruijssen 2007). Some examples of horizontal cooperation in logistics are - as defined by the European Union (2001) - manufacturers consolidation centers (MCCs), joint route planning, and buyers groups. Cooperation provides companies with a platform to access the skills and capabilities of their partners (Kogut 1988; Westney 1988; Hamel 1991). In this way, they can improve their own operational processes by increasing their ability to control costs and to reduce the costs of the supply chain (Gibson et al. 2002).
The proposed tool facilitates contacts and negotiation processes among agents that start acting, in this way, like a community of agents in the district. In fact they can set up groups of agents agreeing on delivery dates, so that more agents can share the same vehicle, reducing consequently the number of vehicles used for shipment. Of course, the filling rate of vehicles increases.
The attractiveness of being a community is related to the increase of utility perceived by agents. In this case, the expected pay-off is made up of rationalization of material flows within the Industrial District.

THE FUZZY APPROACH FOR E-NEGOTIATION

In this paper we assume that a kind of Virtual Coordinator operates in the Industrial District. It helps the district agents to find an agreement about their shipment demand, to achieve the logistics optimization, according to the figure 2. The Virtual coordinator doesn't provides transportation services, it is not a forwarder. It collects shipment demands, submitted by the agents, and creates clusters on the base of the destination's similarity. The Virtual Coordinator is a "place" that allows agent to communicate and negotiate among themselves (for example on shipment date). Therefore agents, after negotiation phase, could ask "together" transport services to a forwarder, optimizing it in terms of monetary and environmental costs.

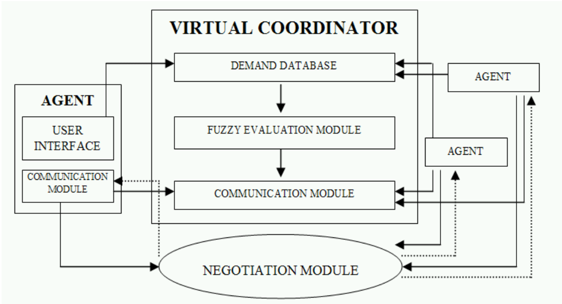

Figure 2 - The Virtual Coordinator

In the following, we explain in detail the e-negotiation phases.

A: Demand database

In our model, the district agents log in the system through the web. They submit to the coordinator the attributes of shipment demands, and give, through the user interface, the following data:

9. destinations;
10. quantity of product to deliver, measured in tonnes;
11. date of delivery, and a tolerance interval in which the agents have to deliver their goods and accept to negotiate about.

The Virtual Coordinator stores these data into a "Demand database" and undertakes the initiative of forming the coalition among interested agents. It helps the agents to reach an agreement, preserving a satisfactory level of system efficiency and fairness.
Table I shows an example of how the attributes of shipment demands are entered.

Table I - Example of introduction of shipment demands

Agent	Destination	Destination Latitude	Destination Longitude	Quantity (t)	Date to deliver	Tolerance Interval
A	Bari, Italy	41° 8' 0"	16° 51' 0"	25	9	7-11
B	Naples, Italy	40° 50' 0"	14° 15' 0"	30	7	5-9
C	Venice, Italy	45° 26' 19"	12° 19' 36"	12	12	9-15
D	Milan, Italy	45° 28' 0"	9° 12' 0"	6	21	19-23
E	Genoa, Italy	44° 25' 0"	8° 57' 0"	50	24	22-26
F	Paris, France	48° 52' 0"	2° 20' 0"	4	24	23-25
G	Berlin, Germany	52° 31' 0"	13° 24' 0"	23	17	14-20

In this table, destinations are defined by their latitude and longitude; quantities of products to deliver are in tonnes; delivery date is entered by clients as a favourite day, and a tolerance interval for dates for delivery.
In relation to the shipment demand attributes, we need to remark that:

12. since Districts are formed on the base of homogeneity of the products, in this paper we are not taken into account the type of them. In other words, we assumed that firms are producing similar products.

13. we have considered only the deliver date (D_a), since the departure day and time (D_{pt}) could be calculated as function of D_a.

B: Destination clusters

At first, the Virtual Coordinator browses the database, picks out from the Fuzzy Evaluation Module (Fig.2) "similar" demands, and clusters them on the basis of closeness of destinations entered by agents. To do it, we have used the Fuzzy C-Mean algorithm in order to define the concept of similarity in a flexible way. In fact, fuzzy optimization can deal with problems having approximate or uncertain data. Indeed, to build a customer's coalition, frequently we need to handle imprecise or lacking information. Therefore, we have used the following algorithm to find a possible coalition, comparing the different demands and finding similarity among them.
Let n be the number of transportation demands submitted to the Virtual Coordinator. These demands are clustered into C clusters (2≤C≤n), homogenous with respect to a suitable similarity measure. The goal is dividing shipment demands in such a way that demands assigned to the same cluster should be as similar as possible (intra-class similarity), whereas two objects belonging to different clusters should be as dissimilar as possible. In the following Table II the relevant pseudo-code is shown:

Table II - The Fuzzy C-Mean pseudo-code

1. Initialize $\mathrm{U} = \lfloor \mu_{ij} \rfloor$ matrix,
2. Calculate the cluster centres (prototypes):

$$c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m \cdot x_i}{\sum_{i=1}^{N} \mu_{ij}^m}$$

3. Compute distances:

$$d_{ij}^2 = \left(x_j - c_i\right)^T \left(x_j - c_i\right)$$

4. Update partition matrix:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(d_{ij} / d_{kj} \right)^{2/(m-1)}}$$

5. $\left\| \mathrm{U}^{(k+1)} - \mathrm{U}^{k} \right\| < \varepsilon$ then STOP; otherwise return to step 2

The algorithm starts choosing just one arbitrary partition P, calculates the cluster centres c_j, and updates partition matrix (P). This process goes on iteratively until partitions are "near enough" each other.
The algorithm shows partitions starting from agents' shipment demands (Table I.). The system stops creating clusters when each cluster is made of only one agent. In figure 3 the clusters resulting from data in Table I are presented. Each cluster is represented by a different colour.

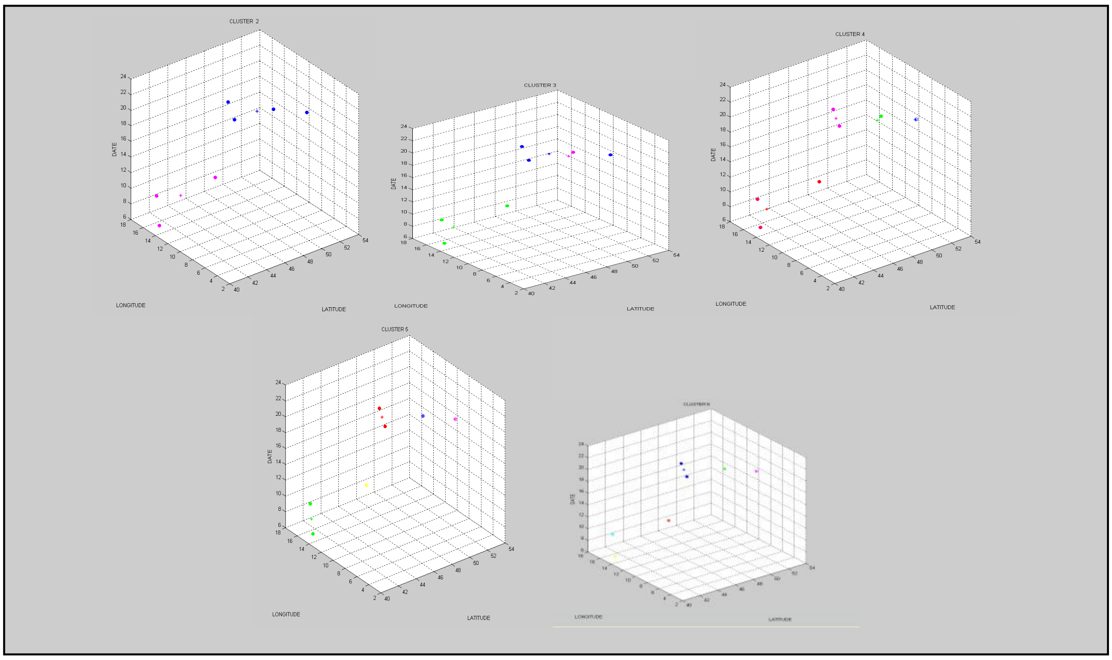

Figure 3 - Clustering procedure

C: Number of shipment units needed

Once number and elements of clusters have been set up, the system calculates the number of shipment units (SU) needed to satisfy shipment demands (eq. 1). SU could be, without distinction from the point of view of the algorithm, containers or trucks for bulk goods. In fact, they represent the bottleneck even in case of multi-modal transport, like for example truck+train. Of course, the operational cost changes case by case. For sake of simplicity, in the following we have considered an uni-modal transport, with trucks as SU.
For the i-th cluster, the system splits the loads into trucks, on the basis of the weight of loads and capacity of the considered trucks. The minimum number of trucks needed is given by the equation(1):

$$SU_i = \text{minimum integer} \geq \Sigma_k(Q_{ki}/C) \qquad (1)$$

in which Q_{ki} is the weight of the k-th shipment demand in the cluster i, and C is the capacity of the average SU.
Of course, when the number of clusters increases, the agents' satisfaction increases as well, but also the number of SU needed to fulfil the transportation demand increases. Considering the average capacity of trucks equal to 25 tonnes, the number of trucks for each cluster represented in fig. 3 is:

14. for partition into 2 clusters: $SU_1 = 3$ $SU_2 = 4$

15. for partition into 3 clusters: $SU_1 = 3$ $SU_2 = 3$, $SU_3 = 1$

16. for partition into 4 clusters: $SU_1 = 3$, $SU_2 = 1$, $SU_3 = 3$, $SU_4= 1$

17. for partition into 5 clusters: $SU_1 = 3$, $SU_2 = 1$, $SU_3 = 1$, $SU_4= 2$, $SU_5= 1$

18. for partition into 6 clusters: $SU_1 = 2$, $SU_2 = 1$, $SU_3 = 1$, $SU_4= 1$, $SU_5= 1$, $SU_6= 3$

D: Optimal number of clusters

The clusters of shipment demands are based on a similarity measure. The system proposes many clustering solutions (see Section B). To find the optimal number of clusters C_O, we have proposed a method that minimizes the Travel Total Cost (*TTC*).
TTC is usually calculated by adding cost of travel time (CTT), and operational cost of trucks (*CUT*).

Calculation of Travel Total Cost (TTC)

On the basis of the clustering process previously carried out, we have calculated for each cluster (from *2* to *6*) the "*Travel Total Cost" (TTC).* The TTC is composed by two different factors.

1. Cost of travel time (CoT)

With an average speed of trucks equal to V_m = 60 km/h, the travel time can be calculated multiplying V_m by the travelled distances (D_i) . Thus, the cost of travel time is (2):

$$CoT_i = V_m \cdot D_i \cdot VoT, \qquad (2)$$

in which VoT = 100€/h is a value of time suitable for Italy.

We calculated, for each cluster, the distance travelled (in Km) from the origin (D_o) to the delivery destination (D_d) and return to origin (D_o), that is twice the distance D_d - D_o. In case of multiple deliveries, the travelled distance is calculated as the sum of distances travelled from origin to the last destination, plus the distance from last destination to the origin.
Once calculated the travelled distances D_i, we can easily calculate $CoT_{i.}$
In our case, with the data of Table I, and considering D_o = Taranto, Italy, we obtained:

19. for partition into 2 clusters: CoT_2 = 86.586.000 €;

20. for partition into 3 clusters: CoT_3 = 86.586000 €;

21. for partition into 4 clusters: CoT_4 = 98.142.000 €;

22. for partition into 5 clusters: CoT_5 = 101.244.000 €;

23. for partition into 6 clusters: CoT_6 = 101.244.000 €.

2. *Operational Cost of Trucks (CUT).*

Calculating the exact operational cost of a truck is out of the aim of this work. From a study by Civitella (1975) came out that in Italy the operational cost per kilometre of a truck is about three times its consumption costs.
Therefore, we calculated first consumption costs (C_u) (3) as sum of fuel cost C_g (4), lubricating oil cost C_l (5), and tires cost C_p(6):

$$C_u = C_g + C_l + C_p \tag{3}$$

in which:

$$C_g = \chi \cdot P_g \cdot f_g \tag{4}$$

$$C_l = 0{,}2 \cdot C_g \tag{5}$$

$$C_p = \beta\, n \frac{P_p + P_r}{S_p + S_r} \tag{6}$$

Where:
n = number of tires per vehicle. We assumed n = 6;
χ = rise coefficient. It varies according to the characteristics of employment and maintenance of vehicle. We assumed χ = 1,40;
P_g = price per litre of fuel. In our case 1,268 €/l;
f_g = average fuel consumption per kilometre. We assumed 4,650 l/km (data from Italian Ministry of Transport).
β = rise coefficient. It varies according to the characteristics of vehicle employment. In our case, we took β = 1,2;
p_p= price of tires. In our case, we assumed p_p = 300,00 €;
p_r= price of tires coating. We assumed p_r = 150,00 €;
S_p= average distance travelled with new tires, assumed equal to 70.000 km;
S_r= average distance travelled with coated tires, assumed equal to 50.000 km.

This way, we have obtained the operational costs according to the following relation (7):

$$CUT = 3\,[Cg + Cl + Cp] \tag{7}$$

In our case:
C_u = 8,3 + 1,7 + 0,027 = 10
CUT = 30
We obtained:

24. for partition into 2 clusters: CUT_1 = 259.740 €, CUT_2 = 1.385.400 €.

25. for partition into 3 clusters: CUT_1 = 113.970 €, CUT_2 = 697.140 €, CUT_3 = 259.740 €.

26. for partition into 4 clusters: CUT_1 = 544.050 €, CUT_2 = 108.810 €, CUT_3 = 113.970 €, CUT_4= 259.740 €.

27. for partition into 5 clusters: CUT_1 = 108.810 €, CUT_2 = 113.970 €, CUT_3 = 142.920 €, CUT_4= 544.050 €, CUT_5= 54.450 €.

28. for partition into 6 clusters: CUT_1 = 108.810 €, CUT_2 = 544.050 €, CUT_3 = 113.970 €, CUT_4= 54.450 €, CUT_5= 125.100 €, CUT_6= 5.940 €.

3. Travel Total Cost (TTC) – results of case study

After we have calculated the cost of travel time and the operational cost of trucks for each partition, we can calculate the TTC_i for every group of cluster by (8):

$$TTC_i = CoT_i + CUT_i \tag{8}$$

In our case, we obtained:

29. for partition into 2 clusters: TTC_2 = **88.231.140** €;

30. for partition into 3 clusters: TTC_3 = **87.656.850** €;

31. for partition into 4 clusters: TTC_4 = **99.168.570** €;

32. for partition into 5 clusters: TTC_5 = **102.208.200** €;

33. for partition into 6 clusters: TTC_6 = **102.196.320** €.

The system considers the clusters with the lowest value of Travel Total Cost (TTC), in our case the partition into 3 clusters. Since each agent could have a variety in dates of delivery, the methodology tries to conciliate the dates preferred by agents belonging to the same cluster. To do this, the system considers "near optimal" divisions of this cluster and proposes to agents a negotiation about it.

E: Negotiation phase

As described in previous sections, agents enter the e-marketplace and submit shipment demands. Agents describe their demands in term of favourite delivery date, destination, and quantity of product to deliver. The Virtual coordinator chooses agents for negotiation by finding the *M* most similar delivery destinations. In this way, each negotiator only negotiates with few opponents, considered to be the most promising. The concept is based on the assumption that a dyad with a high matching degree is likely to reach an agreement more efficiently in further negotiations. Negotiating only with promising opponents minimizes the occurrence of pointless negotiations and hence increases the rate of successful contracts.
The purpose of this method is to enhance group decision-making outcome. In this section we present our conceptualization of the negotiation system. Since the behaviour and the role

played by each agent are different, we used three *FIS* (*Fuzzy Inference System*) to valuate in linguistic term the possible concessions that the agent can made about the delivery date.
The linguistic terms are qualitative descriptions of attributes and are treated as fuzzy sets for computational purposes.

1. First FIS: availability of agent to negotiate.

We use the first FIS to measure the availability of agents to change the delivery date. The availability is inversely proportional to the distance from favourite date. In fact, the more the preferred date is far from the delivery date proposed by the system, the lower is the availability. In case the demand fits exactly one or more shipment units, the availability is none.
The Fuzzy rules of this first FIS are:

1) If (date) is (far) then (availability) is (low)

2) If (date) is (close) then (availability) is (high)

3) If (date) is (same) or (demand fits exactly shipment units) then (availability) is (none).

2. Second FIS: agent's contractual power.

With the second FIS we evaluate the contractual power (P_C). As group members play different roles in an organization, the relative importance of decision makers may not be the same in a decision group, but some decision makers could be more important than others. Therefore, the relative importance of each decision maker should be considered. We use the quantity of product to delivery to measure P_C. In fact, the higher the quantity is, the higher the contractual power. Moreover, in case the demand fits exactly one or more shipment units, the contractual power is high.
The Fuzzy rules of this second FIS are:

1) If (quantity) is (high) or (demand fits exactly shipment units) then (contractual power) is (high)

2) If quantity is (low) then (contractual power) is (low)

3. Third FIS: agent's concession.

These attributes are entered in the following FIS that defines the possible concession of agents. Implemented rules are:

1) If A is high and P_C low then C_o is max

2) If A is low and P_C low then C_o is medium

3) If A is none and P_C low then C_o is minimum

4) If A is high and P_C high then C_o is medium

5) If A is low and P_C high then C_o is minimum

6) If A is none and P_C high then C_o is none

Where:

A = availability

P_C = contractual power

C_o = concession

According to these rules, when an agent is willing to negotiate, and his contractual power is low, he is more available to change the delivery date proposed at first. Instead, when agent has not availability to negotiate, and has a high contractual power, his interest in negotiating is null.

In our case the Virtual Coordinator sent to the Negotiation module (fig. 2) its best solution, that is partition in 3 clusters. The first cluster is composed by the agents A-B-C, the second by the agents D-E-F and the third by the agent G. The agents have to negotiate their delivery time as follows (Tab. III):

Table III - The results of Fuzzy C-Mean code

Agent	Destination	Quantity (t)	Date to deliver	Tolerance Interval	Date for negotiation
B	Naples, Italy	5	7	5-9	9
C	Venice, Italy	12	12	9-15	
D	Milan, Italy	6	21	19-23	23
F	Paris, France	4	24	23-25	

Through the last FIS we obtained:

34. Agent B and Agent C give medium concession (fig. 4);

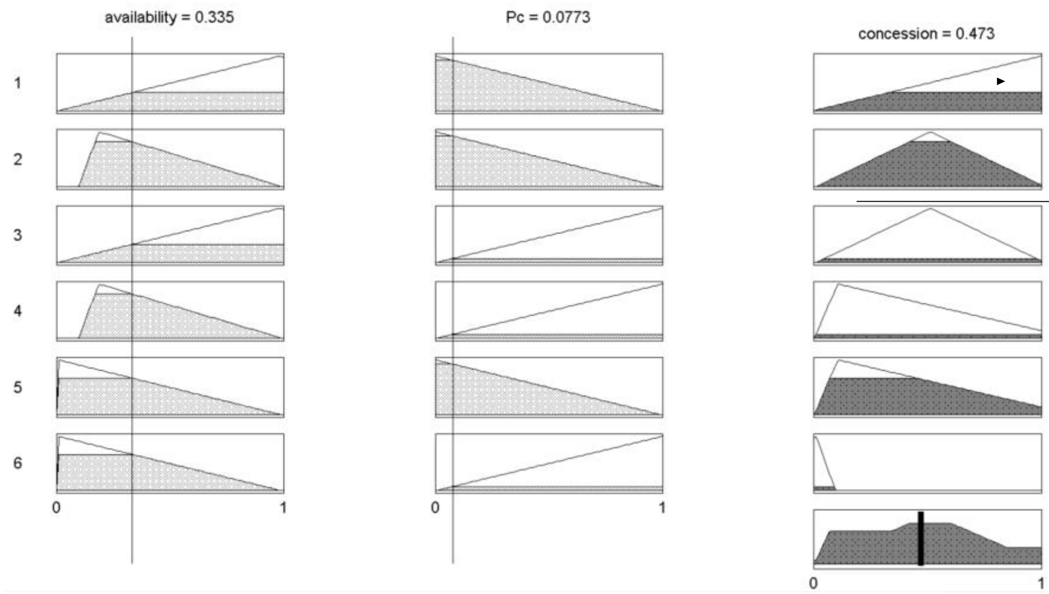

Figure 4 – Agents' B –C - D concession

35. Agent D gives medium concession (fig. 4);

36. Agent F gives max concession (fig. 5).

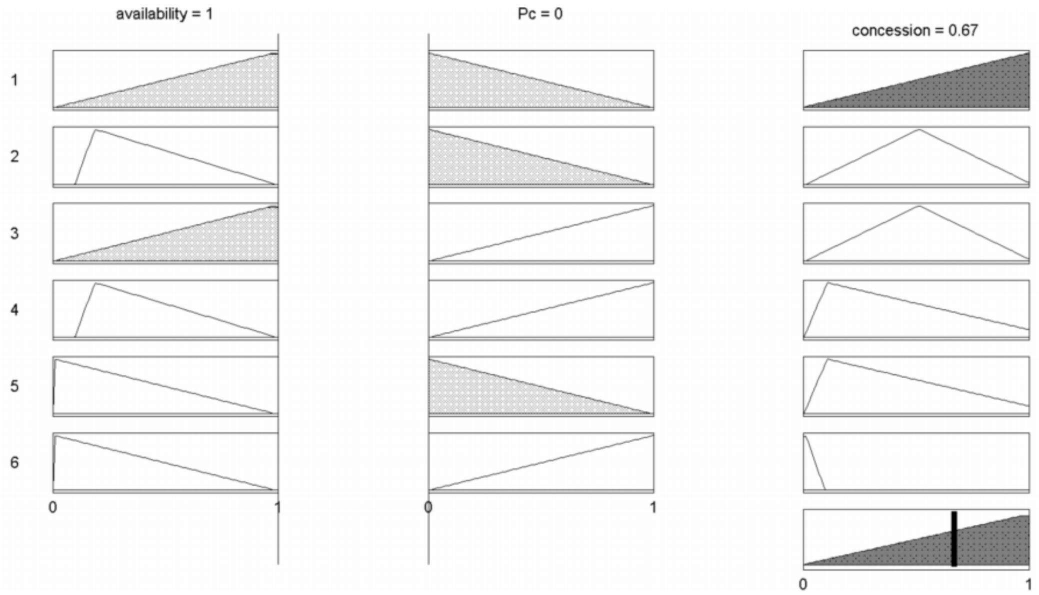

Figure 5 – Agent's F concession

Through the FIS of Agent's Concession, the model has verified that agents could negotiate among themselves (table III). So, it communicates the opportunity to collaborate to the interested agents, which can decide to work together as a community. They can change their shipment date according to what proposed by the model, to achieve economical benefits. In our case of study the agent B and C could decide to use the same truck, and change their delivery date from 7 to 9, and from 12 to 9 respectively. At the same time the agent D and F could decide to change their delivery date from 21 to 23, and from 24 to 23 respectively.
In this way, the agents get an economic benefit as follows:

37. Agent B = from CUT_a = 4.190.850 € To CUT_b = 3.534.644 €

38. Agent C = from CUT_a 10.944.450 € to CUT_b = 8.483.146 €

39. Agent D = from CUT_a = 11.619.810 € To CUT_b = 13.126.104 €

40. Agent F = from CUT_a = 21.870.810 € to CUT_b = 8.750.736 €

Where:

- CUT_a is the shipment cost without collaboration;
- CUT_b is the cost of a "collaborative" shipment. .

In our case study, the agent D seems not getting any advantage from collaboration. However, his counterpart F gets a very high advantage; therefore, the Virtual Coordinator proposes a direct agreement between them in order to partially share the F's advantages and consequently to keep the cluster.

CONCLUSIONS

In this paper we proposed a framework that could be useful to streamline the flow of goods in Industrial Districts. Industrial districts represent a particular context in which cooperation advantages are more evident. In the proposed case the agents can achieve an economical benefit because can put tougher their goods, and divide the cost of shipments.

The proposed system is able to create an e-community, where the agent can meet each other, exchange information and knowledge, and possibly negotiate a compromise among them. In fact, in this context e-negotiation may produce several benefits on the logistic performance due to cooperation among firms belonging to the same industrial district.

A Fuzzy Logic based model for making trade-offs in negotiations in an e-marketplace is also presented in this paper. Conflicting objectives are simultaneously considered through a fuzzy optimization algorithm. Behaviour of agents when making trade-offs are explicitly formulated through fuzzy inference systems.

It appears that this framework can be used to provide real time solutions to complex practical logistics and environmental problems. The proposed architecture makes an agreement among district firms easier, and therefore reduces the number of vehicles used.

Future research will carry out an application of the proposed e-negotiation system on a real case.

REFERENCES

Becattini G., Pyke F., Sengenberger W. (Eds.). 1992. Industrial districts and inter-firm co-operation in Italy. International Institute for Labour Studies, Geneva.

Billington. C. (1994). Strategic supply chain management. OR/MS, Today, 20–27.

Bose, U., A. M. Davey, and D. L. Olson. (1997). "Multi-attribute Utility Methods in Group Decision Making: Past Applications and Potential for Inclusion in GDSS". Omega, 6(25), 691–706.

Bui, T. (1989). Co-oP: A Group Decision Support System for Cooperative Multiple Criteria Group Decision-Making. Springer-Verlag, Berlin

Carbonara N., Giannoccaro I., Pontrandolfo P. (2002) "Supply chains within industrial districts: A theoretical framework" Int. J. Production Economics 76, 159-176

Cheng, Subrahmanian, & Westerberg. (2003). Design and planning under uncertainty: Issues on problem formulation and solution. Computer and Chemical Engineering, 27, 781.

Civitella F. (1975). Automobilismo Industriale. ACI, anno XXIII n. 1-2.

Eom, S. B. (1998). "Relationships Between the Decision Support System Subspecialties and Reference Disciplines: An Empirical Investigation". European Journal of Operational Research 1(104), 31–45.

Hamel, G. (1991), "Competition for competence and interpartner learning within international strategic alliances," Strategic Management Journal, 12, pp. 83-104.

Heiskanen P., Ehtamo H., Hämäläinen R.P. (2001), "Constraint proposal method for computing Pareto solutions in multi-party negotiations". European Journal of Operational Research 133 (1) 44–61.

Henkoff. R. (1994). Delivering the goods. Fortune, 140, (11), 34–47.

Hsu, H. M. and C. T. Chen. (1996). "Aggregation of Fuzzy Opinions under Group Decision-Making". Fuzzy Sets and Systems 2(55), 241–253.

Jarrillo. C.J. (1988). On strategic network. Strategic Management Journal, 9, 31–41.

Kacprzyk, J., M. Fedrizzi, and H. Nurmi. (1992). "Group Decision Making and Consensus Under Fuzzy Preference and Fuzzy Majority". Fuzzy Sets and Systems 1(49), 21–31.

Karacapilidis, N. and T. Gordon. (1995). "Dialectical Planning," Proceedings of 14th International Joint Conference on Artificial Intelligence (IJCAI-95) – Workshop on Intelligent Manufacturing Systems, Montreal, Canada, 239–250.

Kogut, B. (1988), Joint Ventures: "Theoretical and Empirical Perspectives," Strategic Management Journal, 9 (4), pp. 319-332.

Karacapilidis, N. and T. Gordon. (1995). "Dialectical Planning," Proceedings of 14th International Joint Conference on Artificial Intelligence (IJCAI-95) – Workshop on Intelligent Manufacturing Systems, Montreal, Canada, 239–250.

Korhonen, P. and J. Wallenius. (1990). "A Multiple Objective Linear Programming Decision Support System,"Decision Support Systems 6, 243–251.

Krugman, P. (1991). Geography and Trade. MIT Press, Cambridge, MA.

Lai, V. S., B. K. Wong, and W. Cheung. (2002). "Group Decision Making in a Multiple Criteria Environment: A Case Using the AHP in Software Selection". European Journal of Operational Research, 1(137), 134–144.

Lazerson, M.H., Lorenzoni, G. (1999). The firms that feed industrial districts: a return to the Italian source. Ind. Corporate Change 8, 235–266.

Lee, H. M. (1996). "Group Decision-Making Using Fuzzy Set Theory for Evaluating the Rate of Aggregative Risk in Software Development". Fuzzy Sets and Systems, 2(80), 261–271.

Lomi. A. (1991). Reti Organizzative, Teoria, tecnica e applicazioni. Il Mulino, Bologna.

Lorenzoni, G. Ornati O.. (1988). Constellations of firms and new ventures. Journal of Business Venturing, 3, 41–57.

Lu, J. and M. A. Quaddus. (2001) "Integrating Knowledge Based Guidance System with Multiple Objective Decision Making". The New Zealand Journal of Applied Computer and Information Technology 1(5), 53–59.

Maillat D., B. Lecoq, F. Nemeti, M. Pfister. (1995). Technology District and innovation: The case of the Swiss Jura Arc. Regional Studies, 29, (3), 251–263.

Marimin, M., I. Hatono, and H. Tamura. (1998). "Linguistic Labels for Expressing Fuzzy Preference Relations in Fuzzy Group Decision Making", IEEE Transactions on Systems, Man, and Cybernetics, 2(28), 205–217.

Marshall, A. (1925). Principles of Economics. eighth ed. Macmillan, London.

Nishizaki, I. and F. Seo. (1994). "Interactive Support for Fuzzy Trade-off Evaluation in Group Decision-Making,". Fuzzy Sets and Systems, 3(68), 309–325.

Piore, M. Sabel C.. 1984. The second industrial divide: Possibilities for prosperity. Basic Books, NewYork.

Porter. M. (1998). Clusters and the new economics of competition. Harvard Business Review, 76, 77–90.

Pruitt.1981. Negotiation Behavior. Academic Press, New York.

Pyke, F., Sengenberger, W. (1992). Industrial Districts and Local Economic Regeneration. International Institute for Labor Studies, Geneva.

Raiffa. 1982. The Art and Science of Negotiation. Harvard University Press, Cambridge, MA.

Rao, G. R. and M. Turoff. (2000). "A Hypermedia-Based Group Decision Support System to Support Collaborative Medical Decision-Making". Decision Support Systems 2(30), 187–216.

Sakawa, M., H. Yano, and T. Yumine. (1987). "An Interactive Fuzzy Satisficing Method for Multi-Objective Linear Programming Problems and its Application". IEEE Transactions on Systems, Man, and Cybernetics SMC 17, 654–661.

Shim, J. P., M. Warkentin, J. F. Courtney, D. J. Power, R. Sharda, and C. Carlsson. (2002). "Past, Present, and Future of Decision Support Technology". Decision Support Systems 2(33), 111–126.

Vogel, D., R. Davison, and R. Shroff. (2001). "Socio-Cultural Learning: A Perspective on GSS Enabled Global Education". Communications of AIS 9(7), 1–41.

Westney, D. (1988), "Domestic and Foreign Learning Curves in Managing International Cooperative Strategies," In Contractor, F. and P. Lorange (Eds.), Cooperative Strategies in International Business. Lexington Books, Toronto.

Wooldridge, N.R. Jennings. (1995). Intelligent agents: Theory and practice, Knowledge Engrg. Rev. 10, (2), 115–152.

Young, O.R. (1975). "Strategic interaction and bargining" in O.R. Young (ed.), "Bargaining: formal theories of negotiation". Urbana: University of Illinois Press.

Zadeh, L. A. (1965). "Fuzzy Sets," Inform and Control. 3(8), 338–353.

Zhang, G. Q. and J. Lu. (2002). "Group Decision Making Method with Fuzzy Preference of Decision Makers". The International Conference of Group Decision and Negotiation, Perth, Australia, 26–28, August, 2002.

Zimmermann, H. J. (1987). Fuzzy Sets, Decision Making and Expert Systems. Kluwer-Nijhoff Publishing, Dordecht.

Gibson, B., S. Rutner, and S. Keller (2002), "Shipper-carrier partnership issues, ranking and satisfaction," International Journal of Physical Distribution and Logistics Management, 32 (8), pp. 669-681.

Becattini G., Pyke F., Sengenberger W. (Eds.). 1992. Industrial districts and inter-firm co-operation in Italy. International Institute for Labour Studies, Geneva.

Billington. C. (1994). Strategic supply chain management. OR/MS, Today, 20–27.

Bose, U., A. M. Davey, and D. L. Olson. (1997). "Multi-attribute Utility Methods in Group Decision Making: Past Applications and Potential for Inclusion in GDSS". Omega, 6(25), 691–706.

Bui, T. (1989). Co-oP: A Group Decision Support System for Cooperative Multiple Criteria Group Decision-Making. Springer-Verlag, Berlin

Carbonara N., Giannoccaro I., Pontrandolfo P. (2002) "Supply chains within industrial districts: A theoretical framework" Int. J. Production Economics 76, 159-176

Cheng, Subrahmanian, & Westerberg. (2003). Design and planning under uncertainty: Issues on problem formulation and solution. Computer and Chemical Engineering, 27, 781.

Civitella F. (1975). Automobilismo Industriale. ACI, anno XXIII n. 1-2.

Dullaert, Fleuren, Cruijssen (2007). "Horizontal cooperation in transport and logistics: a literature review". Transportation Journal.

Eom, S. B. (1998). "Relationships Between the Decision Support System Subspecialties and Reference Disciplines: An Empirical Investigation". European Journal of Operational Research 1(104), 31–45.

Gibson, B., S. Rutner, and S. Keller (2002), "Shipper-carrier partnership issues, ranking and satisfaction," International Journal of Physical Distribution and Logistics Management, 32 (8), pp. 669-681.

Hamel, G. (1991), "Competition for competence and interpartner learning within international strategic alliances," Strategic Management Journal, 12, pp. 83-104.

Heiskanen P., Ehtamo H., Hämäläinen R.P. (2001), "Constraint proposal method for computing Pareto solutions in multi-party negotiations". European Journal of Operational Research 133 (1) 44–61.

Henkoff. R. (1994). Delivering the goods. Fortune, 140, (11), 34–47.

Hsu, H. M. and C. T. Chen. (1996). "Aggregation of Fuzzy Opinions under Group Decision-Making". Fuzzy Sets and Systems 2(55), 241–253.

Jarrillo. C.J. (1988). On strategic network. Strategic Management Journal, 9, 31–41.

Kacprzyk, J., M. Fedrizzi, and H. Nurmi. (1992). "Group Decision Making and Consensus Under Fuzzy Preference and Fuzzy Majority". Fuzzy Sets and Systems 1(49), 21–31.

Karacapilidis, N. and T. Gordon. (1995). "Dialectical Planning," Proceedings of 14th International Joint Conference on Artificial Intelligence (IJCAI-95) – Workshop on Intelligent Manufacturing Systems, Montreal, Canada, 239–250.

Kogut, B. (1988), Joint Ventures: "Theoretical and Empirical Perspectives," Strategic Management Journal, 9 (4), pp. 319-332.

Korhonen, P. and J. Wallenius. (1990). "A Multiple Objective Linear Programming Decision Support System,"Decision Support Systems 6, 243–251.

Krugman, P. (1991). Geography and Trade. MIT Press, Cambridge, MA.

Lai, V. S., B. K. Wong, and W. Cheung. (2002). "Group Decision Making in a Multiple Criteria Environment: A Case Using the AHP in Software Selection". European Journal of Operational Research, 1(137), 134–144.

Lazerson, M.H., Lorenzoni, G. (1999). The firms that feed industrial districts: a return to the Italian source. Ind. Corporate Change 8, 235–266.

Lee, H. M. (1996). "Group Decision-Making Using Fuzzy Set Theory for Evaluating the Rate of Aggregative Risk in Software Development". Fuzzy Sets and Systems, 2(80), 261–271.

Lomi. A. (1991). Reti Organizzative, Teoria, tecnica e applicazioni. Il Mulino, Bologna.

Lorenzoni, G. Ornati O.. (1988). Constellations of firms and new ventures. Journal of Business Venturing, 3, 41–57.

Lu, J. and M. A. Quaddus. (2001) "Integrating Knowledge Based Guidance System with Multiple Objective Decision Making". The New Zealand Journal of Applied Computer and Information Technology 1(5), 53–59.

Maillat D., B. Lecoq, F. Nemeti, M. Pfister. (1995). Technology District and innovation: The case of the Swiss Jura Arc. Regional Studies, 29, (3), 251–263.

Marimin, M., I. Hatono, and H. Tamura. (1998). "Linguistic Labels for Expressing Fuzzy Preference Relations in Fuzzy Group Decision Making", IEEE Transactions on Systems, Man, and Cybernetics, 2(28), 205–217.

Marshall, A. (1925). Principles of Economics. eighth ed. Macmillan, London.

Nishizaki, I. and F. Seo. (1994). "Interactive Support for Fuzzy Trade-off Evaluation in Group Decision-Making,". Fuzzy Sets and Systems, 3(68), 309–325.

Piore, M. Sabel C.. 1984. The second industrial divide: Possibilities for prosperity. Basic Books, NewYork.

Porter. M. (1998). Clusters and the new economics of competition. Harvard Business Review, 76, 77–90.

Pruitt.1981. Negotiation Behavior. Academic Press, New York.

Pyke, F., Sengenberger, W. (1992). Industrial Districts and Local Economic Regeneration. International Institute for Labor Studies, Geneva.

Raiffa. 1982. The Art and Science of Negotiation. Harvard University Press, Cambridge, MA.

Rao, G. R. and M. Turoff. (2000). "A Hypermedia-Based Group Decision Support System to Support Collaborative Medical Decision-Making". Decision Support Systems 2(30), 187–216.

Sakawa, M., H. Yano, and T. Yumine. (1987). "An Interactive Fuzzy Satisficing Method for Multi-Objective Linear Programming Problems and its Application". IEEE Transactions on Systems, Man, and Cybernetics SMC 17, 654–661.

Shim, J. P., M. Warkentin, J. F. Courtney, D. J. Power, R. Sharda, and C. Carlsson. (2002). "Past, Present, and Future of Decision Support Technology". Decision Support Systems 2(33), 111–126.

Vogel, D., R. Davison, and R. Shroff. (2001). "Socio-Cultural Learning: A Perspective on GSS Enabled Global Education". Communications of AIS 9(7), 1–41.

Westney, D. (1988), "Domestic and Foreign Learning Curves in Managing International Cooperative Strategies," In Contractor, F. and P. Lorange (Eds.), Cooperative Strategies in International Business. Lexington Books, Toronto.

Wooldridge, N.R. Jennings. (1995). Intelligent agents: Theory and practice, Knowledge Engrg. Rev. 10, (2), 115–152.

Young, O.R. (1975). "Strategic interaction and bargining" in O.R. Young (ed.), "Bargaining: formal theories of negotiation". Urbana: University of Illinois Press.

Zadeh, L. A. (1965). "Fuzzy Sets," Inform and Control. 3(8), 338–353.

Zhang, G. Q. and J. Lu. (2002). "Group Decision Making Method with Fuzzy Preference of Decision Makers". The International Conference of Group Decision and Negotiation, Perth, Australia, 26–28, August, 2002.

Zimmermann, H. J. (1987). Fuzzy Sets, Decision Making and Expert Systems. Kluwer-Nijhoff Publishing, Dordecht.