



A community of agents as a tool to optimize industrial districts logistics

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Abstract

The aim of this paper is to find an optimal solution to operational planning of freight transportation in an industrial district. We propose a system architecture that drives agents – the industrial district firms - to cooperate in logistic field, to minimize transport and environmental costs. The idea is to achieve logistics optimization setting up a community made of district enterprises, preserving a satisfactory level of system efficiency and fairness. We address the situation in which a virtual coordinator helps the agents to reach an agreement. The objectives are: maximizing customers satisfaction, and minimizing the number of trucks needed. A fuzzy clustering (FCM), two Fuzzy Inference System (FIS) combined with a Genetic Algorithm (GA), and a greedy algorithm are thus proposed to achieve these objectives, and eventually an algorithm to solve the Travelling Salesman Problem is also used. The proposed framework can be used to provide real time solutions to logistics management problems, and negative environmental impacts.

Keywords: Logistics optimization; Industrial districts logistics; Inter-firms relationship; Fuzzy multi-agents systems.

1. Introduction

Pyke and Sengenberger (1992) describe the main characteristic 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 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 inter-firm relationships in Industrial Districts, such as constellations of firms, flexible specialisation model, milieux innovateurs, firm networks, and clusters. Each model emphasises different and complementary aspects of

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Industrial Districts, yet all of them focus on the features of inter-firm relationships (Carbonara, et al. - 2002). These models show that cooperation among Industrial District firms could represent a way to improve their competitiveness. According to this, in this paper we assert 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, conflicting variables like, for example, the difference between proposed and desired delivery dates, and the number of trucks used have to be optimized. 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 these criteria 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 developed as follows. In the following section there is a short outline of logistics' district management, and the relationships among the industrial district firms. The second section shows an application that achieves the creation of a Logistics Community among district agents. The last section presents a case of study, some final remarks and suggests future developments of the research.

2. The logistic in Industrial Districts

2.1 Logistic problems

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. This stage of the district's evolution process (Formation) is characterized by rare or absent relationships among firms. In fact, each of them tries to get its target by competing with others, increasing the complexity of the system. In Industrial Districts there is frequently a lack of inter-firm relationships: companies don't know each other, so they behave like individual agents. Therefore, "coordination" and "interaction" could represent a chance

to solve logistics optimization problems, taking advantage of possible external economies.

Small firms – as is usual in Industrial Districts - could deal with more problems than big companies in logistics. Usually, small district firms contact one by one transportation services providers, just when they need to deliver their products. In other words, small and medium firms 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.

3. An approach to logistic optimization in an Industrial District

The advantages to be an Industrial District firm are represented by the external economies that the District produces when firms work together. 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. 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).

Our proposed system takes into account conflicts and aggregation situations among group members. The final decision is expected to be the most acceptable by the group of individuals as a whole.

3.1 Proposed solution: Creation of an Agent’s Community

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 assumed that negotiation is more efficient if information is available to all parties. However, this approach requires all parties to surrender part of their privacy, that is to reveal their shipment demand attributes. Since they are basically unwilling to disclose private information during a negotiation (Heiskanen et al., 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 provided by other agents. The information match is done by the Virtual Coordinator, as explained in the following sections.

We have considered both vertical and horizontal relationships power in supply chains. Although logistics cooperation 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. In fact, a participant may use information to improve its market position at the

expense of other participants (Dullaert et al., 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.

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.

3.2 Methodology

In decision-making practice, individual preferences are often expressed through linguistic terms, which reflect imprecise values. Thus, precise mathematical models could be not able to easily tackle such situations. Instead, Fuzzy Logic 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 about agents preferences. Therefore, in this paper we have proposed a fuzzy approach.

The Fuzzy Logic was introduced by Zadeh (1965). More recently, approaches for aggregating fuzzy opinions in multiple criteria decision-making were investigated (Kacprzyk, 1992). The basic principle is grounded on the degree of membership (M_d) of an element x to a set A . In classical crisp logic, the membership function can take only two values: if x is a member of A , then M_d is 1; otherwise, M_d is 0. Instead, in Fuzzy Logic an element x can be "partially" included into a set A , so the value of its Membership Function belongs to interval $[0,1]$.

In this paper we use the Fuzzy C-mean for the cluster creation, and the Fuzzy Inference Systems (FIS) for evaluating the agent's satisfaction, and the "goodness" of solution, as explained in the following paragraphs.

3.3 Fuzzy C – mean : Clusters formation

We have used the Fuzzy C-mean to find a possible coalition among district's agents, comparing their different demands and finding similarity among them. The similarity concept could involve imprecise evaluations: for example, in case of goods transportation, similarity of two different demands could be measured through the distance between their shipment dates. This distance could be defined using linguistic statements such as: "far" or "close". In this case, the closer the dates, the more similar are the demands. Fuzzy C-means (FCM) algorithm is thus useful to handle these imprecise values, to find similarity among different demands, and consequently to find possible coalitions.

Let n be the number of transportation demands submitted by agents. These demands are clustered into C clusters ($2 \leq C \leq n$), 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, whereas two objects belonging to different clusters should be as dissimilar as possible. However, fuzzy clustering algorithms usually require that the number of clusters be previously defined by the user (Höppner

et al., 1999). This is quite restrictive in practice, since the number of clusters in a data set is generally unknown, especially in real-world data involving overlapping clusters. In order to get around this difficulty, in our case the system makes clusters from 2 to n.

In other words, when the agents' shipment demands $n = 5$, the Fuzzy C-mean clusters them into 2, 3, 4, and 5 clusters, according to the similarity of demands. The value of μ_{ij} indicates the degree of membership to C_i cluster for each agent.

In the following Table 1 the relevant pseudo-code is shown:

Table 1: The Fuzzy C-Mean pseudo-code.

1. Initialize $U = [\mu_{ij}]$ matrix,
2. Calculate the cluster centers :

$$c_j = \frac{\sum_{i=1}^N \mu_{ij}^m \cdot x_i}{\sum_{i=1}^N \mu_{ij}^m}$$
3. Compute distances:

$$d_{ij}^2 = (x_j - c_i)^T (x_j - c_i)$$
4. Update partition matrix:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$$
5. $\|U^{(k+1)} - U^k\| < \varepsilon$ 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 U. This process goes on iteratively until partitions are “near enough” each other.

In the following, we show an example of matrix U when the shipment demands are 5.

Table 2: U similarity matrix.

$U_2 = \begin{bmatrix} 0.9 & 0.06 \\ 0.9 & 0.05 \\ 0.5 & 0.4 \\ 0.01 & 0.9 \\ 0.8 & 0.1 \end{bmatrix}$	$U_3 = \begin{bmatrix} 0.8 & 0.07 & 0.02 \\ 0.9 & 0.06 & 0.02 \\ 0.01 & 0.9 & 0.01 \\ 0.0001 & 0.0001 & 0.9 \\ 0.45 & 0.44 & 0.09 \end{bmatrix}$
$U_4 = \begin{bmatrix} 0.8 & 0.08 & 0.03 & 0.01 \\ 0.7 & 0.2 & 0.05 & 0.02 \\ 0 & 0.0001 & 0.9 & 0 \\ 0 & 0 & 0 & 1 \\ 0.002 & 0.9 & 0.002 & 0.0007 \end{bmatrix}$	$U_5 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

The number of rows is equal to the total number of demands, and the number of columns is equal to the number of clusters considered.

3.4 Fuzzy Inference System : The evaluation of agents satisfaction, and the “goodness” of solution

The finding of the best clustering solution requires efficient criteria to quantitatively measure the quality of the solutions (Milligan, M.C. Cooper, 1985). Several criteria for fuzzy clustering assessment have been proposed in literature (see for example Halkidi, et al., 2001).

This paper proposes a new “cluster validity measure” as a criterion to help the decision making process for managing logistic district problems. We evaluate the solution on the basis of the results made by two Fuzzy Inference Systems (FIS).

The first one measures the agents satisfaction for the solution proposed by the algorithm. The degree of satisfaction of each solution is calculated using a set of fuzzy rules. The input variable in our system is the favourite day for the delivery, along with a range of dates. The closer the delivery date proposed by the system to the favourite date, the higher the satisfaction. The input can be divided in the three Fuzzy set, as illustrated in Figure 1. Note that in this figure the variable “date” is normalized, that is its values have been rescaled in the range [0,1], taking into account minimum and maximum values, in order to make the system adaptable for all possible intervals and to simplify the modeling process.

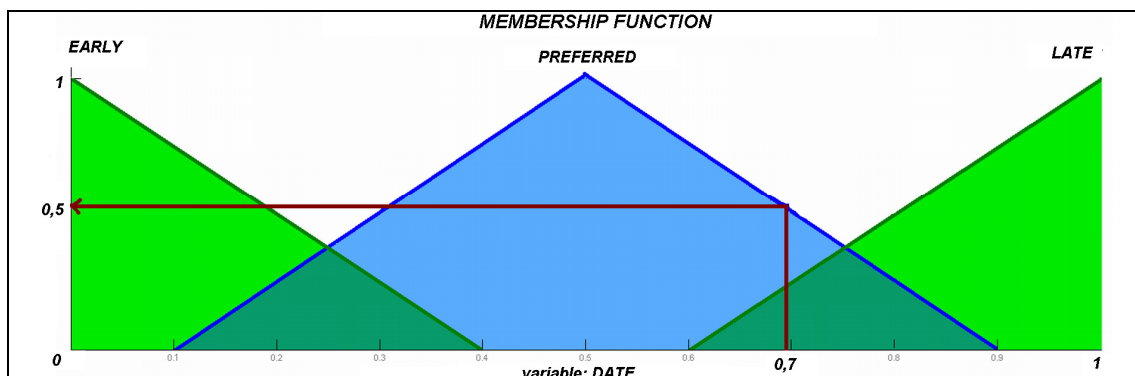


Figure 1: Membership functions.

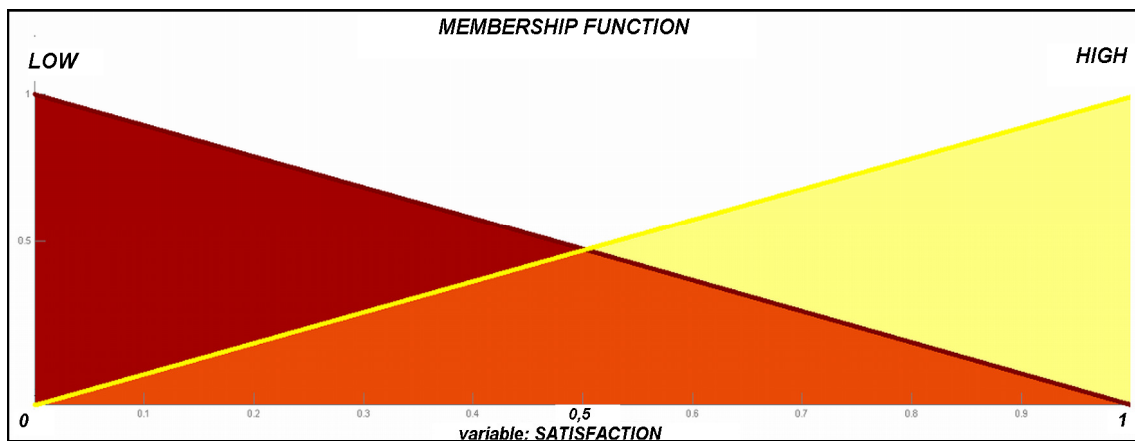


Figure 2: Membership functions.

In order to set the satisfaction for the delivery date, proposed by system after the optimization, we also have to define the output “satisfaction” which includes two attributes, *low* and *high*, as shown in Figure 2.

We can calculate the degree of satisfaction, using the following set of fuzzy rules:

- If date is early then satisfaction is low*
- If date is late then satisfaction is low*
- If date is preferred then satisfaction is high*

The satisfaction level is one of the input variables for the second FIS, which measures the “goodness of the solution”. The second input is the number of trucks, which has two fuzzy values: many and few. Then, the goodness of solution is calculated through the following set of rules:

- If trucks are many then solution is bad*
- If trucks are few then solution is good*
- If satisfaction is low then solution is bad*
- If satisfaction is high then solution is good*

3.5 The framework

In this paper we assume that a kind of Virtual Coordinator helps the district agents to find an agreement about their shipment demand, to achieve the logistics optimization. The Virtual Coordinator creates the agents’ community, but doesn’t provides transportation services, it is not a forwarder. It collects shipment demands, submitted by the agents, and creates clusters on the basis of the destination’s similarity. In other words, the Virtual Coordinator is a “place” that allows agent to communicate and negotiate among themselves, for example about shipment date. Therefore agents, after negotiation phase, could ask "together" transport services to a forwarder, optimizing monetary and environmental costs.

Figure 3 illustrates this process that will be explained, step by step, in the following sections:

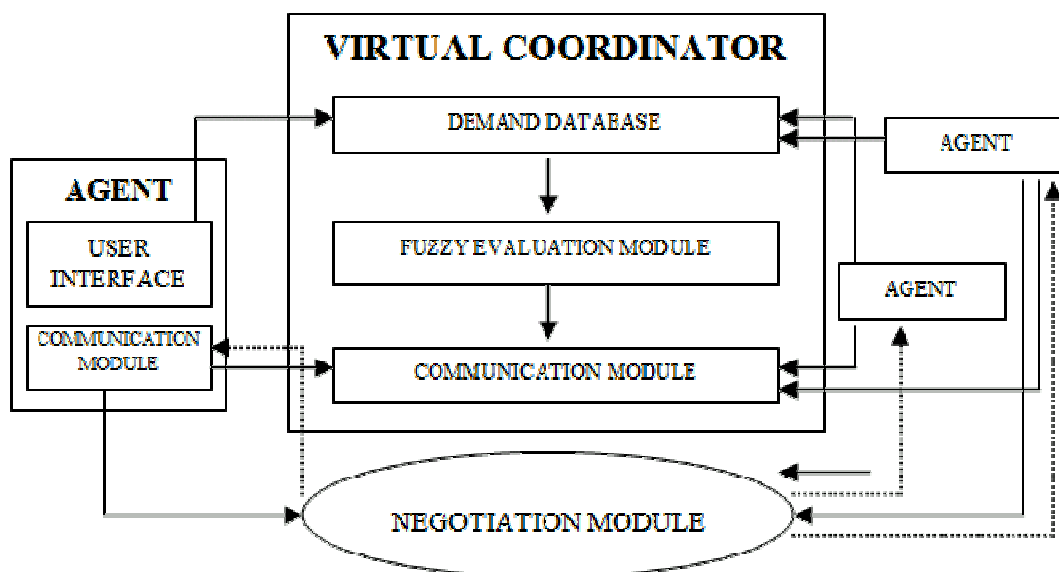


Figure 3: The Virtual Coordinator.

The proposed process can be divided in four steps:

1. submission of demands by the district agents;
2. clustering formation through the Fuzzy C-mean algorithm;
3. calculation of number of Shipment Unit needed;
4. finding possible solutions and choice of a “good solution” through the Fuzzy Inference System.

3.6 First step: The Demand database

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

- destinations;
- quantity of product to deliver;
- a favourite day to deliver and a range of dates in which the agent considers acceptable the delivery;

The Virtual Coordinator stores these data into a “Demand database” (Figure 3), 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.

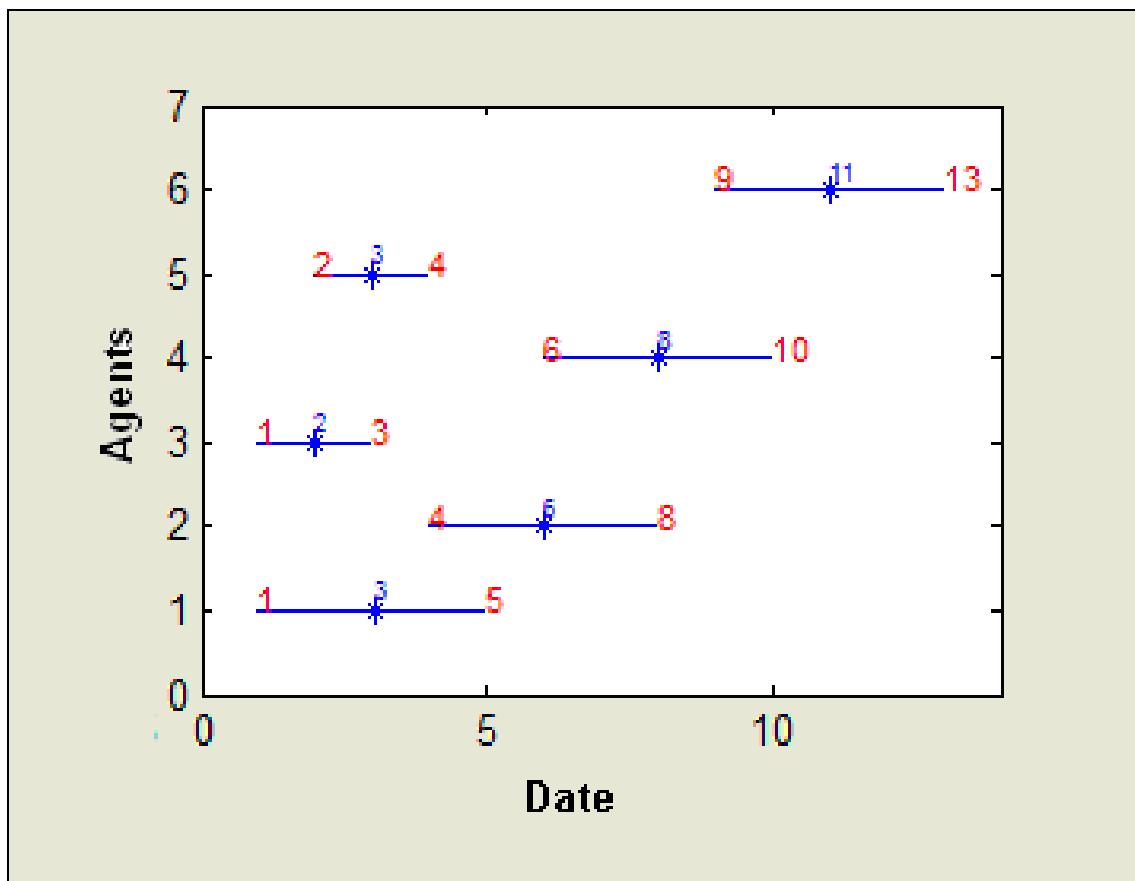


Figure 4: An example of time ranges and “favourite day”(*).

In the Demand Database:

- 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.

As for shipment demand attributes, we need to remark that:

- since districts are formed on the basis of homogeneity of the products, in this paper we did not take into account their type. In other words, we assumed that firms are producing similar products,
- we have considered only the delivery date (d_d), since the departure day and time are calculated as a function of d_d ,

the system accepts only symmetric ranges, therefore the favourite day should be the centre value of the range, which must be at least one day after and one before the “favourite day” (Figure 4).

The system puts all data into a matrix called “U”.

3.7 Second step: Forming the clusters of demands through the Fuzzy C-Mean algorithm.

At first, the Virtual Coordinator browses the database, and picks out from the Fuzzy Evaluation Module (Figure 3) “similar” demands and clusters them on the basis of closeness of destinations and similarity of range of delivery dates entered by agents.

The algorithm shows partitions starting from agents’ shipment demands. The system stops creating clusters when each cluster is made of only one agent.

3.8 Third step: 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. 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 for this cluster is given by the equation (1):

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

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.

3.9 Fourth step: The Fuzzy/Genetic Algorithm.

After the Fuzzy C-mean clustering, a Fuzzy/Genetic algorithm (FA/GA) has been used. GAs have been widely used in the optimization field. In our logistic optimization problem we chose to use a GA because it presents the following advantages:

- no need to know a lot about the function being optimized while searching for its maximum;
- possibility to find the solution after examining surprisingly a small number of states;
- possibility to obtain better results repeating the evolution, since many operations are carried out randomly.

There are three main aspects to take into account to implement the algorithm on an optimization problem: (i) the encoding of the solution; (ii) the definition of the fitness function, and (iii) the implementation of the basic genetic operations (selection, crossover and mutation) within the problem. Through selection, crossover and mutation among cluster members, the algorithm finds the nearest optimal solution. In this application to logistic systems, the population has been initialized as random binary strings. Selection of individuals to be replaced is done according to “elitism method” in which worst individuals are replaced by the best individual. Mutation and crossover process starts from a situation in which all the individuals are the same. The procedure restarts iteratively, until the best value of fitness function is found, or the number of iterations exceeds a fixed threshold. In Table 3 the relevant pseudo-code is reported.

Table 3: The Fuzzy/genetic algorithm pseudo-code.

```

BEGIN
  Create initial population
  Calculate individual fitness
  WHILE NOT finished DO BEGIN
    BEGIN
      Select new population (elitism)
      Crossover between two individuals
      Mutation of single individuals
      Calculate the descendants' fitness
    END
    IF stop condition is satisfied THEN
      finished:= TRUE
    END
  END
END

```

Genetic algorithm creates few combinations. They give the optimal solution based on fitness calculation (Tab. 3). In this paper, a combination of GA and FA is used. It allows to add the advantages of the GA, analyzing and finding several different solutions/combinations of population/shipment demands, to the advantages of FIS, which estimates the fitness (satisfaction) of the agents. This process evolves the population (shipment demands) until a solution is found. The FA/GA algorithm generates more solutions and evaluates each solution according to its fitness.

The “best” solution is found by two Fuzzy Inference Systems (FIS). The first FIS finds the agents’ satisfaction, on the basis of the closeness of proposed solution to the favourite day entered by the agent.

The second FIS calculates the “goodness” of solution, based on the maximization of agents’ satisfaction, and minimization of the number of trucks needed. This system has two inputs: the “satisfaction” calculated through the first Fuzzy Inference System, and the “number of truck” needed to fulfil the shipments demands. Afterwards, the system optimizes truck loading through a greedy algorithm. The greedy value is given by:

$$r = (d_1 - a_1) / c_{\max}$$

where:

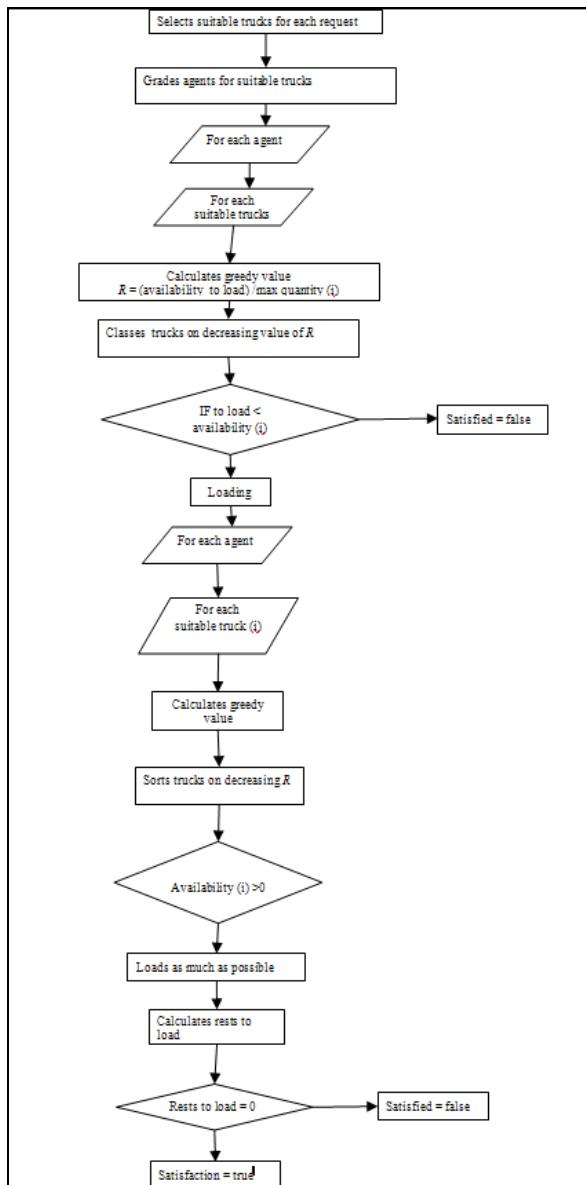
d_1 = availability to load

a_1 = weight of goods to load

c_{\max} = capacity of a truck

In the table below (Table 4) the relevant pseudo - code is illustrated.

Table 4: The Greedy algorithm pseudo-code.



The algorithm loads trucks so that the load split for each agent is as small as possible. Finally, the proposed system solves a Travelling Salesman Problem to minimize the delivery route.

3.10 Results

The system finds out the possible members of the coalition among agents with similar transportation demands. The Virtual Coordinator submits to agents the set of clusters having the best performance in terms both of number of trucks needed and agents' satisfaction. On their turn, agents can accept the proposed solution or, through a negotiation module (Figure 3), can change the demand attributes. The system shows to agents the negotiation changes (Figure 3), and any agent could decide individually to change his tolerance about delivery date, fulfilling a not completely full truck and thus reducing the shipment costs. Otherwise, they could reduce or increase the load amount, and thus agree with another cluster member having same shipment destinations, to take advantage in using a truck completely full. In this case, the procedure restarts with formation of new clusters.

4. A practical example

In our case of study we have hypothesized an industrial district located around the city of Taranto, in Apulia region, Southern Italy, formed by seven agents. The agents submit their shipment demands to the Virtual Coordinator.

4.1 The demand database

The district agents enter their shipment demands attributes, as shown in the following Table 5.

Table 5: Case of study: shipment demands database.

<i>Agent</i>	<i>Destination</i>	<i>Destination Latitude</i>	<i>Destination Longitude</i>	<i>Quantity (t)</i>	<i>Date to deliver</i>	<i>Tolerance Interval (dates)</i>
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

4.2 Clustering shipment demands

Afterwards, the Virtual Coordinator creates the agents community. In the Fuzzy Evaluation Module, the Fuzzy C-mean algorithm collects the seven shipment demands

and clusters them on the basis of the “similarity” of the destinations, and the range of dates for delivery. In our case, the algorithm shows partitions in two, three, four, five, six, and seven clusters. In Figure 5 the clusters resulting from these data, as listed in Table 5, are presented. Each cluster is represented by a different colour.

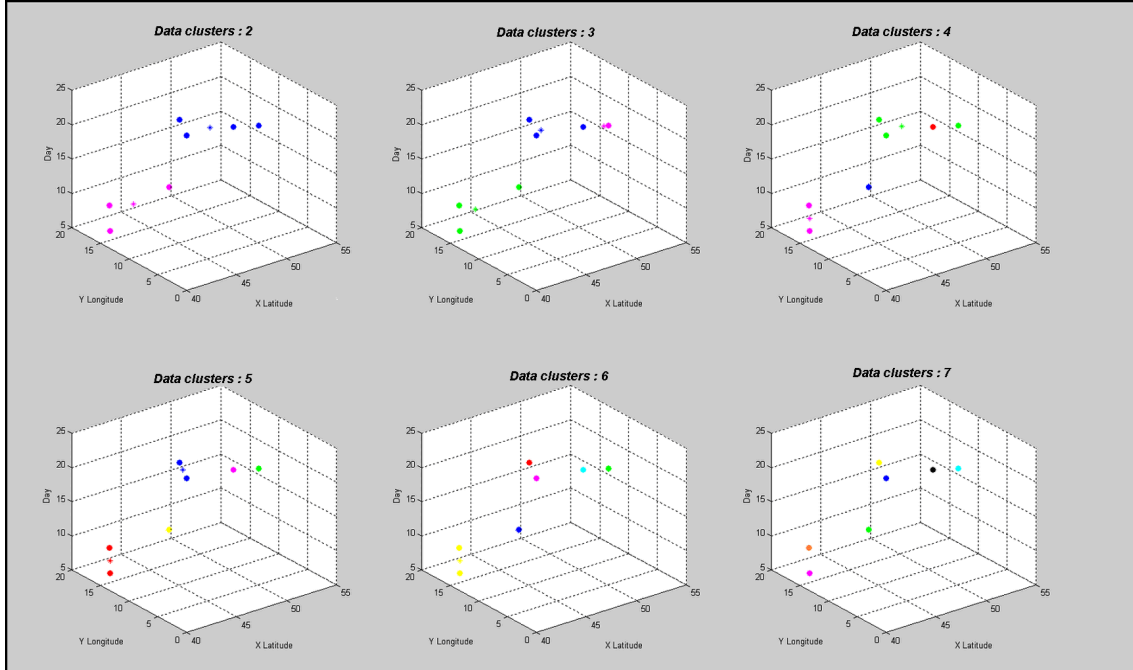


Figure 5: Case of study: clustering procedure.

4.3 Calculation of the number of trucks

For sake of simplicity we consider an average truck having capacity of 25 tonnes. The number of trucks for each cluster calculated by the system is reported in the following. In Figure 6, an example of result window for three partition is represented.

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

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

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

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

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

for partition into 7 clusters: $SU_1 = 1, SU_2 = 2, SU_3 = 1, SU_4 = 1, SU_5 = 2, SU_6 = 1, SU_7 = 1$

4.4 The proposed solutions and their evaluation

The possible solutions are found through the fuzzy/genetic algorithm, which select the best solutions, for each cluster, through two FIS.

Figure 6 shows an example of results given by the algorithm in case of three partitions.

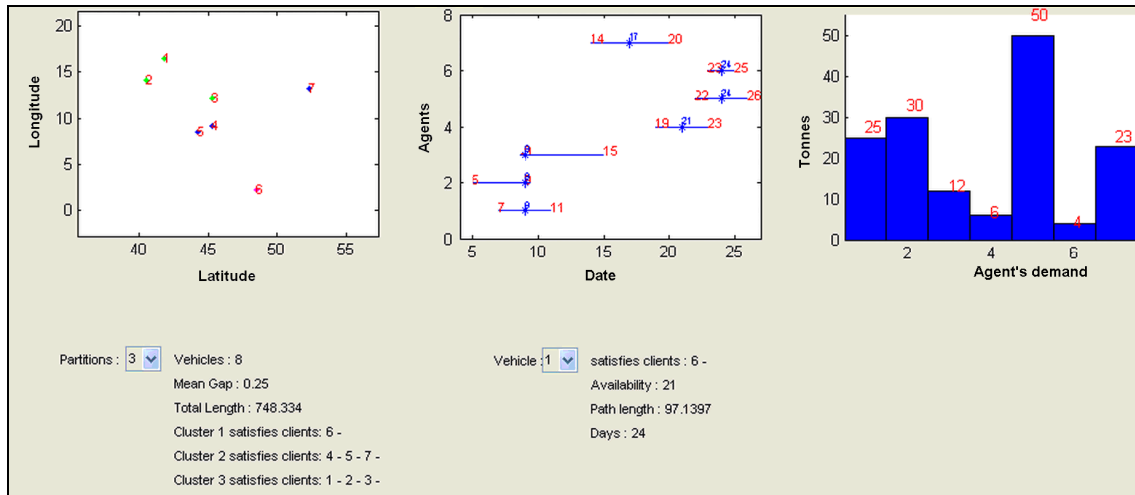


Figure 6: An example of proposed solution for three partition. Window A.

Through the window represented in Figure 6, one can actually select the number of partitions (from 2 to n). In the example, three partitions have been selected, and the figure shows that the total load is divided into eight trucks. Also, agents belonging to each cluster are indicated. In the right side of the figure, one of the eight trucks needed can be selected. For the selected truck, the system shows the clients satisfied, the availability (21 tonnes in this case), and the date for the delivery (day 24).

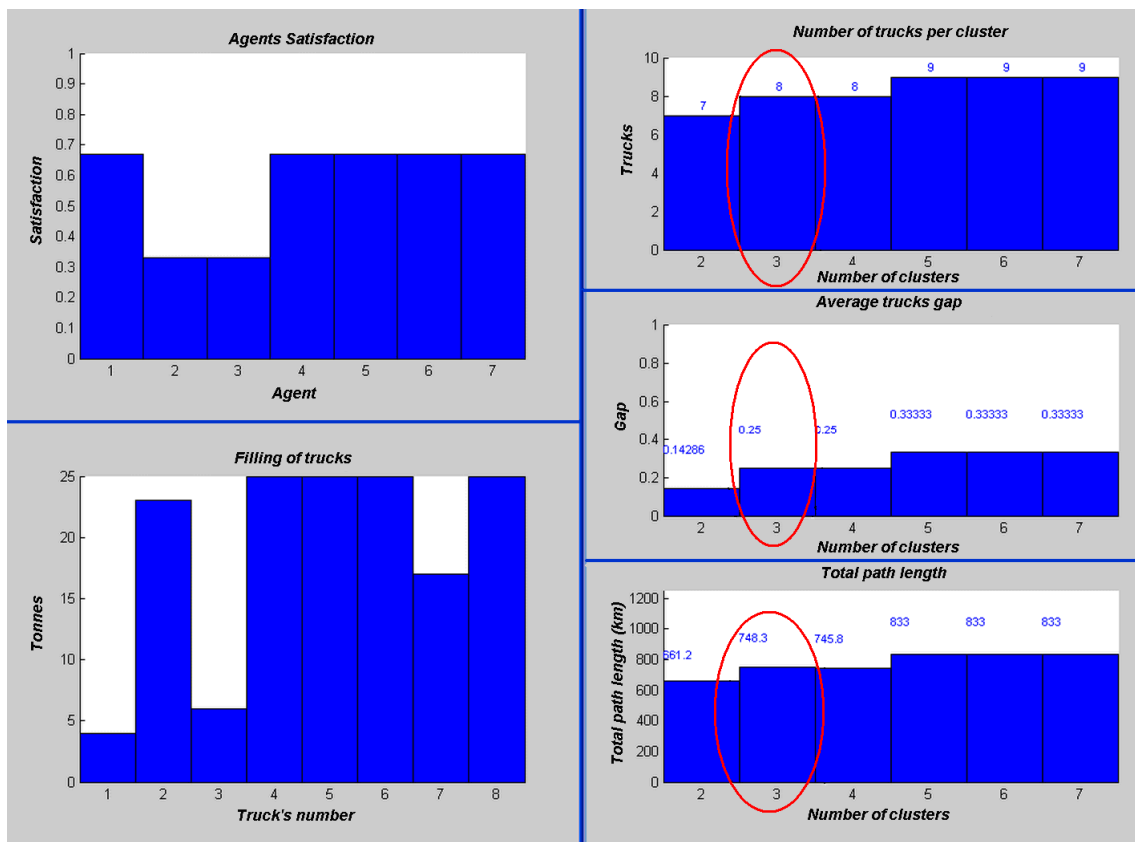


Figure 7: An example of proposed solution for three partitions. Window B.

In another window (Figure 7) are illustrated: in the left side, the satisfaction of each agent, and the filling rate of each truck for partition into three clusters; in the right side, the number of trucks needed for each cluster, the average capacity of trucks not filled up (average trucks gap), and the path length for each cluster are highlighted for partition into three clusters.

These information are important in negotiation phase, because each agent involved in it could decide whether to accept the proposed solution or, and possibly how, change its shipment demand.

5. Conclusion and future developments

In this paper we have 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 share the cost of shipments.

The proposed system is able to create an e-community, where agents can meet each other, exchange information and knowledge, and possibly negotiate a compromise among them about products shipment. 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. 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 easier the cooperation among district firms in the shipment of their products, reducing the number of vehicles used.

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

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