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Identifying and exploiting the collaboration factors inside SMEs networks

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Abstract: Present research introduces a procedure for the analysis of the collaborative behaviour inside industry networks. Collaboration is seen as a collection of factors, each of them boosting competitive advantages to industry networks of small and medium enterprises (SMEs). The distinctiveness of the research is that there is not a preliminary choice of the technical and organising factors that contribute to establish any forms of collaboration among the SMEs.

As there is a large number of typologies among the industry networks, it has been necessary to highlight the common features and the main interactions with the inside and the outside of the network by building a meta-model of the network organisation. Collaboration factors were extracted applying the non-linear principal components analysis to a large set of data collected by the EU project CODESNET. The extracted collaboration factors become the entries of a modified SWOT analysis. The result of the process is the evaluation of the potential directions of collaboration independent from the specific network type.

Keywords: SMEs network; collaboration; industrial networks; networking; principal component analysis; PCA; SWOT analysis.

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1 Introduction

While an exact definition of industry network is lacking, there is concordance on the main components: in the largest majority of cases networks include only SMEs. Following the European cluster observatory report (2007), 38% of the European employees work in enterprises belonging to clusters and more than 94% of the enterprises are SMEs. The advantage of aggregation for SMEs is the increase in competitiveness on the worldwide market without any losses of autonomy (Albino and Kühtz, 2004; Picard and Toulemonde, 2003; Verwaal and Hesselmans, 2004).

In present work clusters are seen as a mild form of network. We can refer to Bergman and Feser (1999) for the definition of a cluster: "a group of business enterprises and non-business organisations for whom membership within the group is an important element of each member firm's individual competitiveness". Following Rosenfeld (1995), a network is:

> "A group of firms with restricted membership and specific, and often contractual, business objectives likely to result in mutual financial gains. The members of a network choose each other, for a variety of reasons; they agree explicitly to cooperate in some way and to depend on each other to some extent. Networks develop more readily within clusters, particularly where multiple business transactions have created familiarity and built trust."

These definitions are not universally accepted and it is possible to find different appellations for SMEs networks in different countries ('industrial districts' in Italy, 'network of competence' in Germany, 'poles of competitiveness' in France). Different names refer to intrinsic differences among networks, due to specificities in country, production field, destination market. The difference among national SMEs networks can be appreciated by comparing Seliger et al. (2008) for the German network of competence, Paniccia (1999) for the Italian industrial district and Chan and Lau (2005) for the Science Park in Greece.

The diversity among networks is reflected also in the different approaches to the concept of collaboration among competing enterprises. There are several definition for a collaborative network (CN) (e.g., Appley and Winder, 1997; Phillips et al., 2000; Wood and Gray, 1991). These authors agree that collaboration give a boost to both the quality and the profits of the involved enterprises. An inclusive definition is due to Himmelman (1992): collaboration is "a process in which organisations exchange information, alter activities, share resources and enhance each other's capacity for mutual benefit and a common purpose by sharing risks, responsibilities and rewards".

Collaboration can be seen under many different perspectives: Anand and Khanna (2000) highlight the role of collaboration in creating new knowledge or in the mutual transfer of existing one; Wasserman and Galaskiewicz (1994) show the effects of interfirm network structures on organisation, performance and strategic decision making.

As collaboration has so many uncorrelated and non-easily measurable benefits, the result is that academic literature trying to highlight the potentiality of CN is either qualitative or focuses on the economic aspects of collaboration: the only measurable ones. Some studies relate to the comparison of the performances of firms with respect to their belonging to a CN. Signorini (1994) compares the financial and economic ratios of some firms belonging to the industrial district of Prato to the average of woollen cloth manufacturers located outside the province. Fabiani and Pellegrini (1998) analyse the profitability and productivity ratios of firms belonging to districts in comparison with a control sample of similar firms. These and other studies (Molina-Morales, 2001) confirm the hypothesis of positive externalities for SMEs belonging to CN (in terms of ROE, ROI, etc.), but they all consider performances only from the economic point of view.

The enterprise network is a 'social and economic whole' where the success is as dependent on broader social and institutional aspects as on economic factors in a narrow sense (Pyke et al., 1990).

Regarding the operational structure, it is possible to borrow from the wide literature on supply chain performance analysis (Akif et al., 2005; Abu-Suleiman et al., 2005; Klejinen and Smits, 2003). Furthermore, some ascertained tools can be used, as an example the SCOR model (http://supply-chain.org/) or the balanced scorecard (Kaplan and Norton, 1992, 1993, 1996; 1996; Brewer and Speh, 2000).

The difficulty of applying these tools to CNs consists in the lack of formalised collaboration links among enterprises and in the difficulty of obtaining KPIs for the entire network from the analysis of individual firms. As a matter of fact collaboration usually emerges from a series of informal and unplanned relationships among enterprises made easier because of geographic proximity (Hakansson 1990). Some authors dare to state that "many aspects of business relationships can never be formalised or based on legal criteria" (Gadde et al., 2003).

In this paper a formal approach is used to investigate the positive and negative aspects of collaboration in a wide group of networks spread all over Europe. We start from a large data base describing these networks from quantitative and qualitative points of view. The data are condensed and a reduced number of significant components are hence extracted. They are used to build a SWOT analysis describing the opportunities and the risks of the different collaboration mechanisms for every network.

Next section explains how data were gathered in an identical manner for several different classes of networks. Section 3 is devoted to discuss the application of the non-linear principal components analysis (NPCA) to a set of data of different natures (numerical, categorical). Section 4 describes the results of the application of NPCA. Eventually in Section 5, these results are used to produce a SWOT analysis of the networks. This phase is the most sensitive because the applicability of the NPCA results is not straightforward. The limits of present analysis together with the possible applications are the subject of the conclusions.

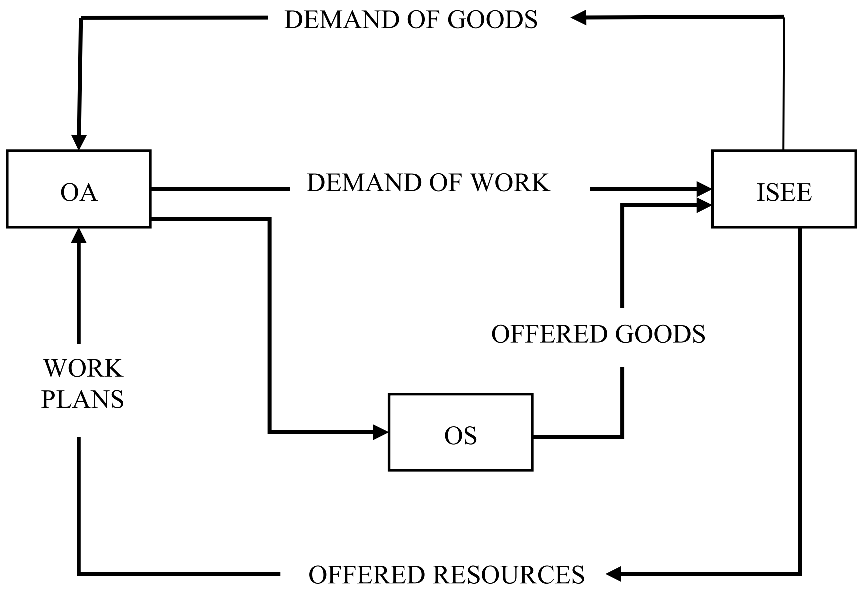
2 Analysing and comparing SME networks

In the majority of SME clusters there is a lack of investments in innovation, due to the lack of an effective governing board able to boost innovation to SMEs. Except for some cases, industrial clusters have not been able to evolve into networks. These issues might originate from the assertion that SMEs do not know how to manage the operations in a network. In this context, the EU funded coordination action CODESNET (collaborative demand and supply network, http://www.codesnet.polito.it) has the goal of giving an organisation and interpretation of data and information collected from the industrial systems of European countries and concerning networks of enterprises for the sake of improving the knowledge about network management (Villa, 2006).

During the development of this project, descriptions for more than 100 industrial networks, coming from 12 different European countries, were collected. The data describe the main aspects of the organisation of the activity production of the enterprises networks taking into account the territorial environment where they grow.

Data and information were organised in a standardised form in order to have a homogeneous catalogue. To do this a network meta-model has been introduced to support the data collection (Antonelli et al., 2006). A scheme of the meta-model is shown in Figure 1.

Figure 1 The meta-model scheme



In this logical representation of an industrial network, three main parts of the system can be highlighted: operation structure (OS), organisation arrangement (OA) and interaction with the socio-economic environment. The OS refers to the graph of interactions linking the enterprises together; the OA concerns the over-firms organisation devoted to manage cooperation of the enterprises together; the interactions with the socio-economic environment (ISEE) refers to the output interface towards external agents (Villa and and Antonelli, 2009).

To describe each elements of this Meta-model and compute the system performances, a list of attributes is necessary in order to identify Performance Indicators that provide directly measurable information; they can be found in Table 1 together with the description of the data metrics. The considered number of KPIs is too large and needs an aggregation strategy.

The distribution of the analysed CNs as a function of the original Country is shown in Figure 2.

Figures 3 and 4 give some descriptive information about the analysed industrial networks. The first histogram (Figure 3) shows that a great part of analysed networks have a number of enterprises in the order of extent of 30; the second histogram (Figure 4) shows the number of employees distributed in the networks.

Table 1 Variables

Variable	*Description*	*Metric*
Firm dimension	Average number of employees per firm	Numerical
Total labour	Total number of employees	Numerical
Skills	Different skills employed in the network	Nominal
Level of production	Sales	Numerical
Logistics quality	Type of logistics involved	Ordinal
ICT	ICT tools	Nominal
Structural model	Type of network configuration	Categorical
Relative importance of SMEs	SME consideration in the network	Ordinal
Coordination	Level of coordination in the network	Ordinal
Cooperation	Level of cooperation in the network	Ordinal
Distribution on the territory	Geographical dimension of the network area	Numerical
External relation	Openness to bodies external to the network	Ordinal
Export	Network international relationships (% of sales)	Numerical
Size of district	Number of SMEs in the network	Numerical
Investment in R&D	Number of R&D programmes	Numerical
Labour market	Network connection to the local population	Ordinal
Degree of communication	Level of communication inside the network and with external bodies	Ordinal
Vision capability	Capability to make long terms planning	Ordinal
Competitiveness	Degree of competitiveness	Ordinal
Transfer knowledge	Capability to transfer knowledge	Ordinal

Figure 2 Nationality of analysed industrial districts

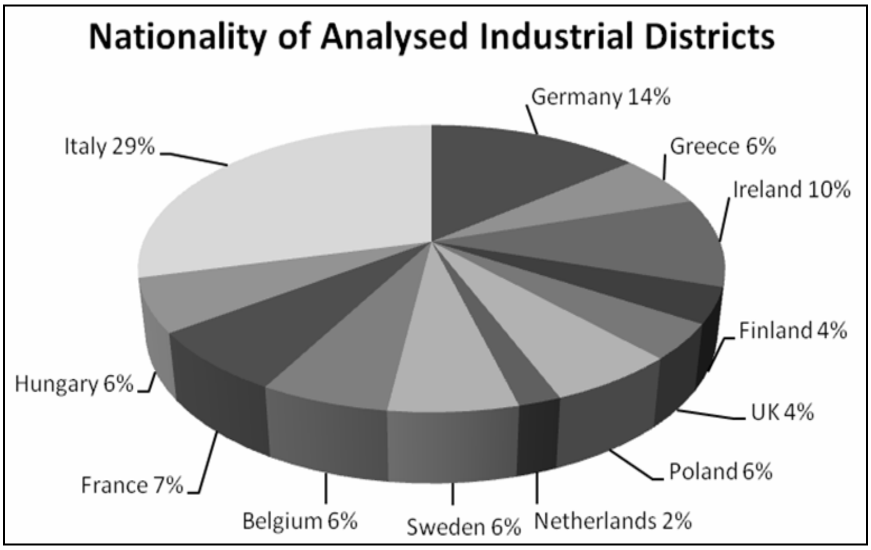


Figure 3 Histogram of number of SMEs in the networks

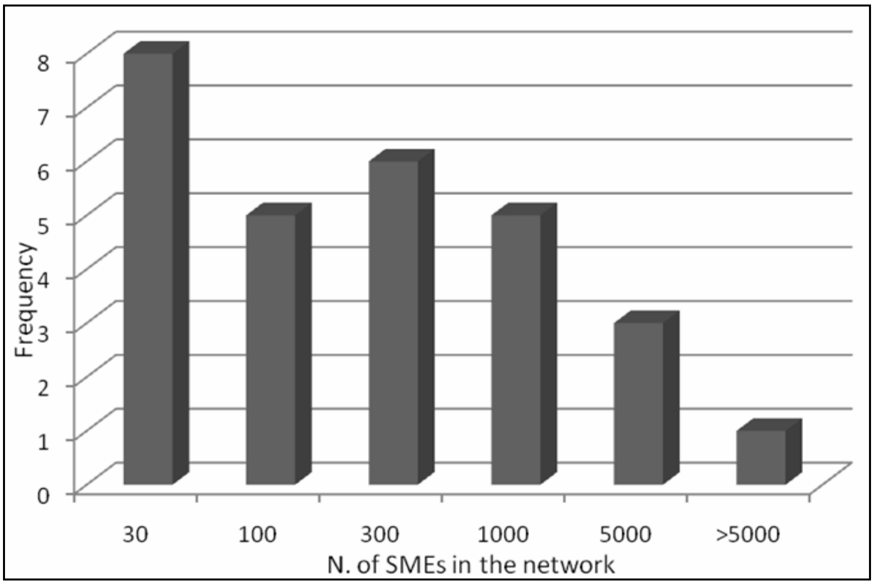
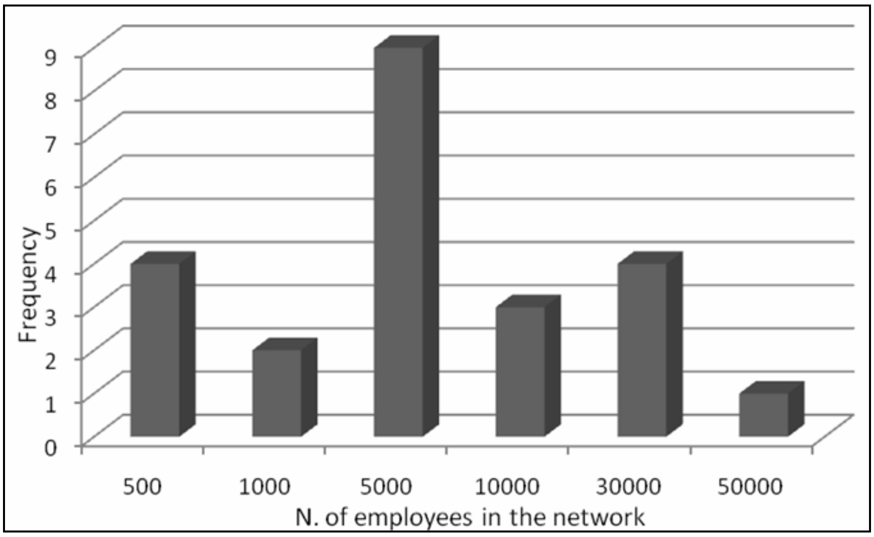


Figure 4 Histogram of number of employees in the networks



It is of no use to classify different networks all over the Europe, using arbitrary indexes, and forming an ordered list with questionable winners and losers. It is much more proficient to state a point of view from which to observe the networks and to try to extract the key factors that influence the network behaviour. Furthermore one must be aware of the fact that data are not disposable only in a quantitative numerical format but also qualitative. Therefore, it is hazardous to use them for scoring.

3 Principal component analysis

An aggregation of original data is necessary. The essential idea of principal component analysis (PCA) is to reduce the observed variables to a number of uncorrelated principal components that reproduce as much variance from the variables as possible. To achieve this objective, PCA transforms the data to a new set of variables, the principal components (PCs) ordered so that the first few components retain most of the variation present in all of the original variables (Jolliffe, 2004).

Data consists of qualitative or categorical variables as well as numerical variables that describe the indicators for a limited number of categories. The relationships among the different categories are unknown, and although some of the variables are composed of categories that are ordered, their mutual distances are still unknown (Gifi, 1981, 1985), therefore it is necessary to have recourse to the non-linear PCA.

In non-linear PCA correlations are not computed between the observed variables, but between their quantification into numeric values through the optimal scaling (Meulman et al., 2004). The objective of this process is to optimise the properties of the correlation matrix, in particular to maximise the first *p* eigenvalues of the correlation matrix, where *p* is the number of components chosen for the analysis. The optimal quantification and the linear PCA model estimation are performed at the meantime. Analysing data with a non-linear PCA requires a dynamic decision making by the researchers about the most appropriate level of analysis.

Programmes that perform non-linear PCA can be found in many statistical packages, for this analysis CATPCA of SPSS software is utilised.

The CATPCA procedure quantifies categorical variables using optimal scaling, resulting in optimal principal components for the transformed variables.

Given:

- a number *n* of analysis cases (objects), in our case industrial districts
- a set of *m* analysis variables
- a number *p* of orthogonal dimensions ($p \leq m$).

An orthogonal linear transformation is applied to transform the data into a new system of coordinates (the principal components) such that the greatest variance by any projection of the data comes on the first component, the second greatest variance on the second principal component and so on.

The CATPCA objective is to find the object (statistic units) scores *X*, i.e., the coordinates of each statistic unit with respect the p principal components, and the categories quantification $\underline{Y}$ for nominal variables, so that the objective function

$$f\left(X,\underline{Y}\right)=n^{-1}\sum_{j}p^{-1}\,tr\left(\left(X-G_j\underline{Y}_j\right)^{¢}M_j\left(X-G_j\underline{Y}_j\right)\right) \tag{1}$$

Under the normalisation restriction $X'M_*X = nmI$ is minimal.

G_j is the indicator matrix with as row as the objects number and as column as the number of categories of variable j:

$$G_{(j)ir} = \begin{cases} 1 & \text{when the } i\text{th object is in the } r\text{th category of variable } j \\ 0 & \text{when the } i\text{th object is not in the } r\text{th category of variable } j \end{cases} \tag{2}$$

M_j is a diagonal matrix which elements are defined:

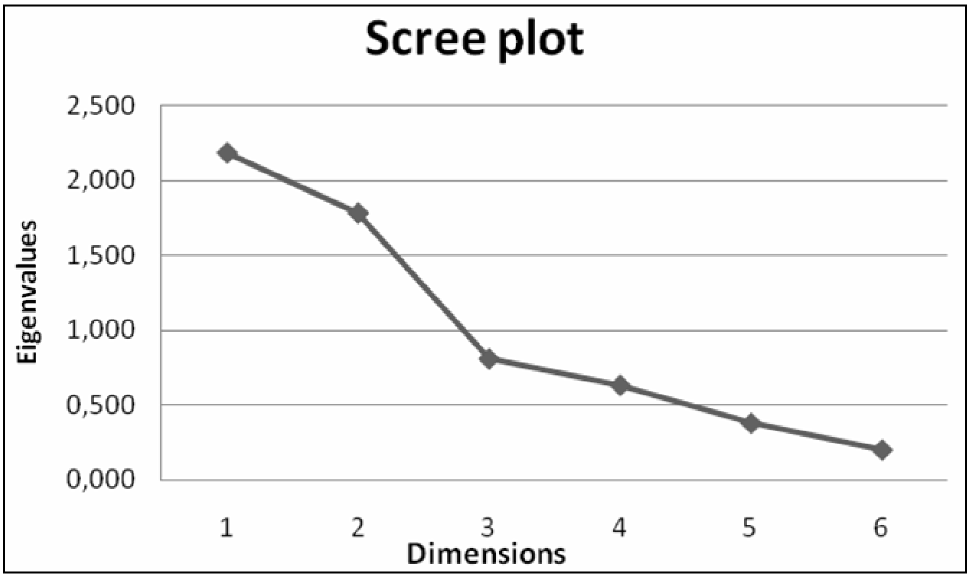
$$M_{(j)ii} = \begin{cases} 0 & \text{when the } i\text{th observation is missing} \\ 0 & \text{when the } i\text{th object is in the } r\text{th category of variable } j \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

3.1 Dimensions reduction to principal components

The first step of the PCA, after having quantified the categorical variables, is to verify that each variable is at least mildly correlated with the other variables, otherwise they are left outside the PCA. Next step is deciding how many components should be used to best describe the variables. The problem is solved by initially analysing data with a number of dimensions equal to the number of variables. Using the equivalence results in having a plot in which each dimension is described by a variable. When a dimension is eliminated the others account for less and less variability. The decision of when to stop extracting factors basically depends on when there is a small variability left. The nature of this decision is arbitrary; however, various guidelines have been developed. The two guidelines used in this research are the Kaiser criterion and the scree plot. They have been applied together to force a more reliable decision. The Kaiser criterion says that only dimensions with eigenvalues greater or equivalent to 1 must be retained. In essence this is like saying that, unless a factor explains at least as much variance as the equivalent of one variable, it should be left out. This criterion was proposed by Kaiser in 1960 but it is still one of the most used methods. The second method is called the scree test which is a graphical method. The method proposed by Cattell requires the eigenvalues to be plotted in a simple line graph as shown in Figure 5. This is a plot with eigenvalues on the ordinate and component number on the abscissa. In a scree plot, scree refers to those components that are at the bottom of the sloping plot of eigenvalues versus component number. The plot provides a visual aid for deciding at what point including additional components no longer increases the amount of variance accounted for by a nontrivial amount. The plot shows the eigenvalues of Table 3 in a graph. Cattel suggests finding the place where the smooth decrease of eigenvalues appears to level off to the right of the plot. To the right of this point is presumable to find only factorial scree, i.e., only a small part of the whole variance that is explainable by the dimensions.

The analysis has been replicated three times, one time for each meta-model component. Results are presented in the following where the component plot is showed. Component loading plot consists in a graph representing a vector for each variable, the coordinates of the end point of each vector are given by the loadings, i.e., the components of each variable with respect the two principal components. Because the cosine of the angles between the vectors equals the correlation between the quantified variables and vectors are long (indicating good fit), variable that are close together in the plot are closely and positively related.

Figure 5 Scree plot



4 Application of PCA to the set of CNs

Now it is possible to attempt a link between the Collaboration dimensions and the meta-model dimensions of the network representation. Referring to Childerhouse et al. (2003) it is possible to classify the following collaboration levels:

- ad hoc – collaboration does not go beyond the traditional customer supplier relationship
- defined and linked – collaboration focuses on operational issues and limited to collaborative planning, forecasting and replenishment of materials and capacities, i.e., supply chain management
- integrated and extended – collaboration at a strategic level where integrated and coordinated strategies lead to strategic synergy, i.e., extended and virtual enterprises.

These levels of collaboration fit perfectly with the three structures present in the meta-model, namely the OA, OS and ISEE. Therefore collaboration can be studied by its influence on the three structure of the network separately.

Variables have been divided into three sets, one for each component of the meta-model. We will show in detail the analysis application for the first set of variables corresponding to the OS component. Variables used to evaluate the OS of an industrial network are listed in Table 1 with a brief description and their typology. In Table 2, an example of values is given together with the possible range for the categorical variables.

Table 2 An example: the Canelli industrial district of wine

Variable	*Example*	*Possible values*
Firm dimension	8	(2 ÷ 50,000)
Total labour	5,584	(6 ÷ 500,000)
Skills	(0, 1, 1, 0, 1, 0, 0, 1, 0)	(Consult. eng., IT, logistics, marketing, production, research, science, technician)
Level of production	€495,000,000	Any
Logistics quality	External	(External or internal)
ICT	(0, 0, 0, 1, 0, 1)	(Administrative tools, drawing tools, EDI, ERP, internet platform, WEB)
Structural model	Supply chain	(Economic association, SME, knowledge district, R&D cooperation, SC, Virtual network)
Relative importance	1	(0:Equal, 1:leaders)
Coordination	Coordinator	(Administration, coordinator, committee, partners)
Cooperation	Contract	(Contract, know-how exch., info exch., agreements, meetings)
Distribution on the territory	Small bounded geographical area	(Small bounded geographical area, large area, EU, global)
External relation	Very high	*
Export	80%	%
Size of district	700	(1 ÷ 3,500)
Investment in R&D	Medium	*
Labour market	High	*
Degree of communication	Low	*
Vision capability	Medium	*
Competitiveness	Low	*
Transfer knowledge	Low	*

Note: *Very high, high, medium, low and absent.

Table 3 Covariance matrix

	Firm dimension	*Total Labour*	*Skills*	*Level of Production*	*Logistics*	*ICT*
Firm dimension	1	0.635	0.012	0.235	–0.059	–0.245
Total labour	0.635	1	–0.019	0.628	–0.290	–0.185
Skills	0.012	–0.019	1	–0.59	0.292	–0.58
Level of production	0.235	0.628	–0.59	1	–0.261	–0.137
Logistics	–0.059	–0.290	0.292	–0.261	1	–0.235
ICT	–0.245	–0.185	–0.58	–0.137	–0.235	1
Dimension	1	2	3	4	5	6
Eigenvalues	*2.185*	*1.783*	0.811	0.635	0.382	0.204

In the covariance matrix (Table 3) is apparent that just two eigenvalues are greater than one, so, according the Kaiser criterion, the best number of dimensions is two. Plotting the eigenvalues on a simple line graph (as shown in Figure 5) it is possible to apply the scree test and obtain that the number of correct dimension would be two or maybe three. By putting together the indications of the two criterions it is easily decided that the optimal number of dimensions is two for the analysis of the first set of variables.

In the covariance matrix we can underline that the variation of the 'total labour', defined in terms of total number of employees in the network, is reasonably high positively related with both the production of the Network and the medium dimension of the firms, while the use of ICT tools is negatively related with the skills of the network because of the difficulty to mix different kinds of experiences in a common way.

After having verified how many dimensions are necessary in the PCA, two in this case, the CATPCA algorithm is followed. The first information obtained from the output of the analysis is the component loading table (Table 4) which can be interpreted by comparing the values for each variable on every dimension.

Table 4 OS: variables components with respect to the principal dimensions

	Dimensions	
	1	*2*
Firm dimension	0.777	0.144
Total labour	0.982	–0.074
Skills	0.012	0.888
Production	0.792	–0.124
Logistics	–0.367	0.584
ICT	–0.333	–0.855

The result of this simple observation is that Dimension 1 mainly explains division of labour, total labour and production, whilst on Dimension 2 the variables that can be projected are Skills, ICT and Logistics. The variables are well grouped on each dimension and are almost orthogonal in the same directions as the dimensions.

From Figure 6, it's clear that a skill employed in the district is positioned near the vertical zero, which undoubtedly results in assigning it to Dimension 2, on the positive side. Conversely, ICT is explained mainly by Dimension 2, on the negative side, although it has a very slight projection on Dimension 1. The larger component stands on Dimension 2. The same can be said about Logistics, which is found in the same direction of Skills. The difference here is that logistics is not as strong in explaining Dimension 2 as Skills is, but still gives a better understanding of the result. On Dimension 1, other three variables are present, but all of them are collinear and also close to the horizontal zero. In this second case, if the variables are analysed carefully a possible definition for Dimension 1 can be the term district dimension, as the variables projected on it all give a description, in different terms, of the size of the industrial district. On the other axis, the main focus is on the skills involved in the district, that are characterised by the industrial functions involved and the ICT tools used. The name that can be proposed for Dimension 2 is then district skills.

Figure 6 OS: component plot

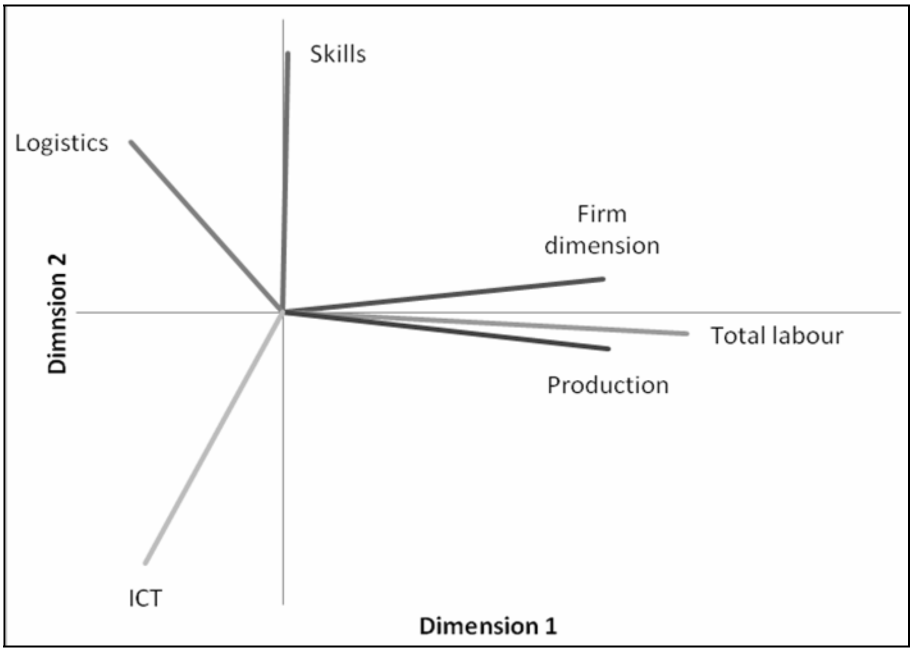
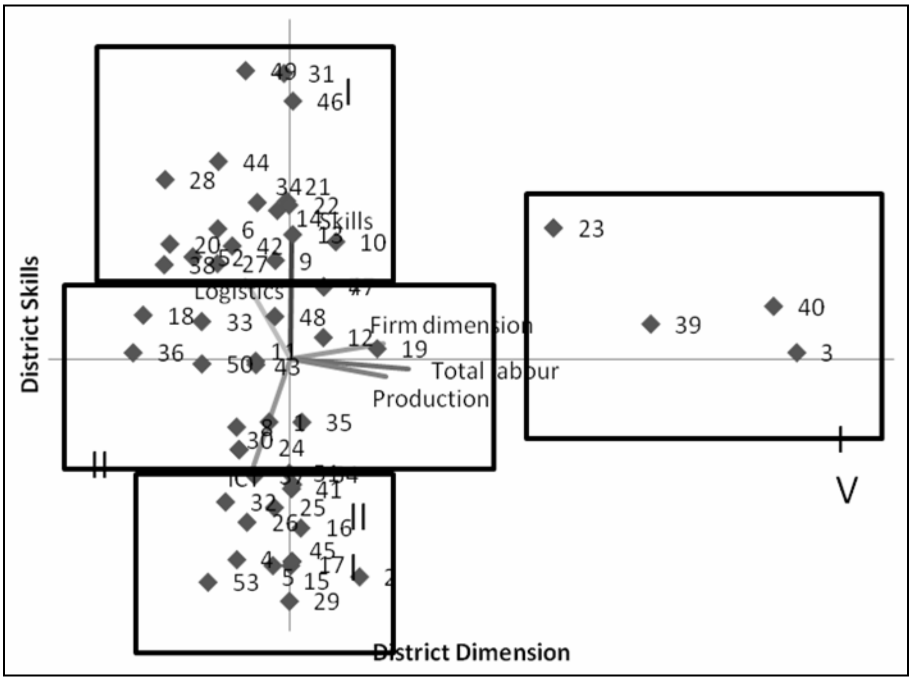


Figure 7 OS: biplot

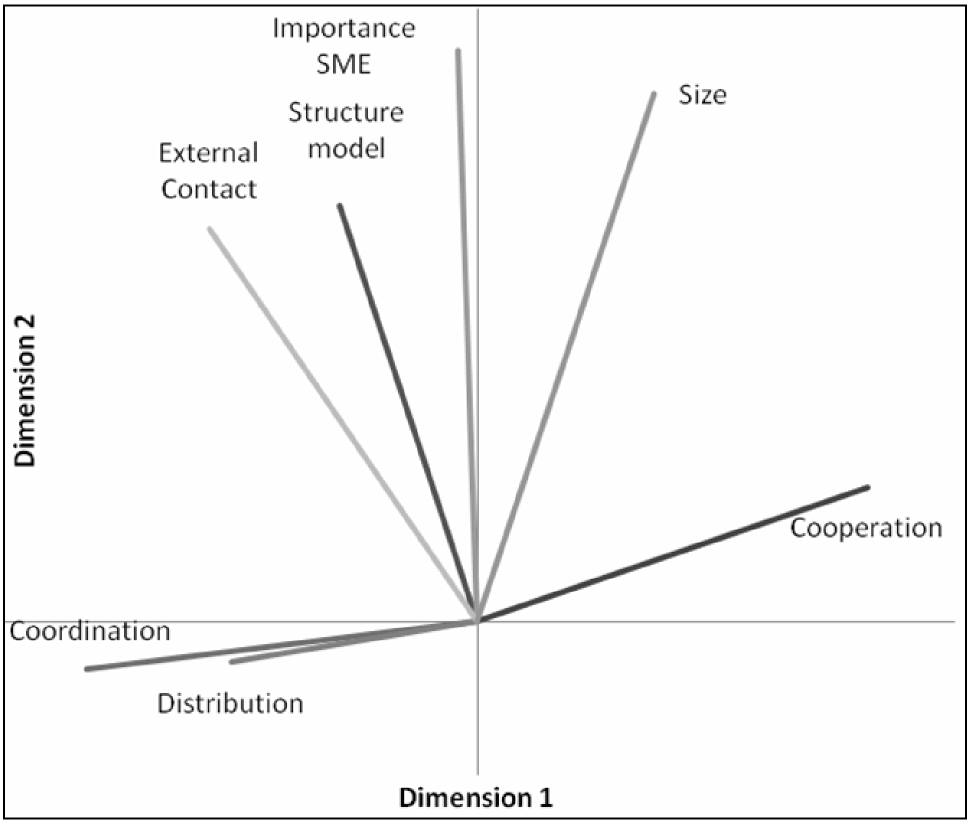


In Figure 7, both the old variables and the objects (industrial networks scores) in the new space, having as dimensions the two principal component, are represented; this representation is called biplot and it shows each district according to its most significant characteristics. The position of the IDs illustrates how the more important discriminating factor lies on the vertical axis, as on the horizontal one there is a very low distribution.

What actually differentiates the clusters is the difference in skills employed in the SMEs. Exceptions are a few IDs that are positioned on the far right of the plot. These outliers have such an important explanation on the dimension axis because they are large supply chains, for which the describing parameters of the dimensions are a few orders of magnitude larger than any other district. The final step of the analysis of the results is to create groups among the clusters. This is done by observing the biplot and by creating clusters of IDs that have similar characteristics. In Group I there are Districts with a variety of skills employed, this mainly happens in District of excellence in their sector and with a particular care to R&D (i.e., Loire Numerique, France) and collaboration with University. Group III is characterises by an important role of ICT where the product of the District is mainly a service.

The same procedure has been followed for the remaining two components of the meta-model. In the OA analysis, the non-linear PCA produces the component plot of the set of variables of Figure 8.

Figure 8 OA: component plot

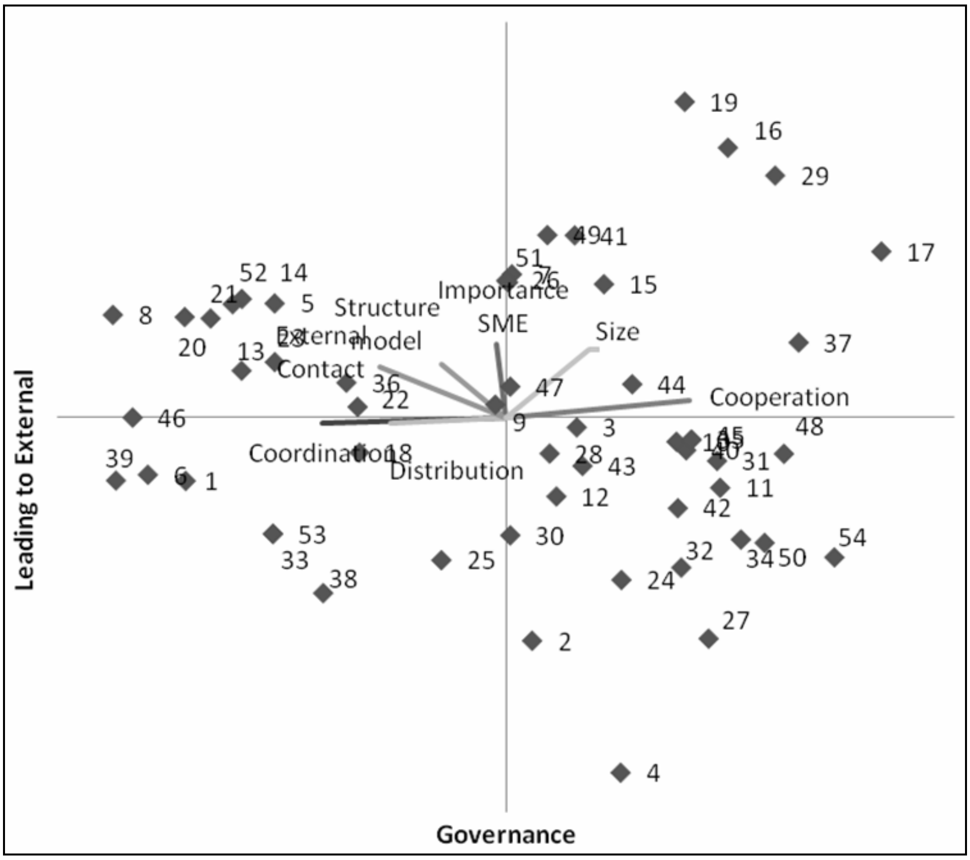


Dimension 1 is defined by the governance type so it can be called Governance, remembering that a positive value means that the main concern is cooperation, whilst a negative value indicates coordination.

Dimension 2 is described mainly either by the market radius or by the existence of leaders in the SME so it can be called Leading to external, where a positive value indicates a leader and large global market and vice versa on the negative side of the axis.

The biplot with the objective scores is shown in Figure 9.

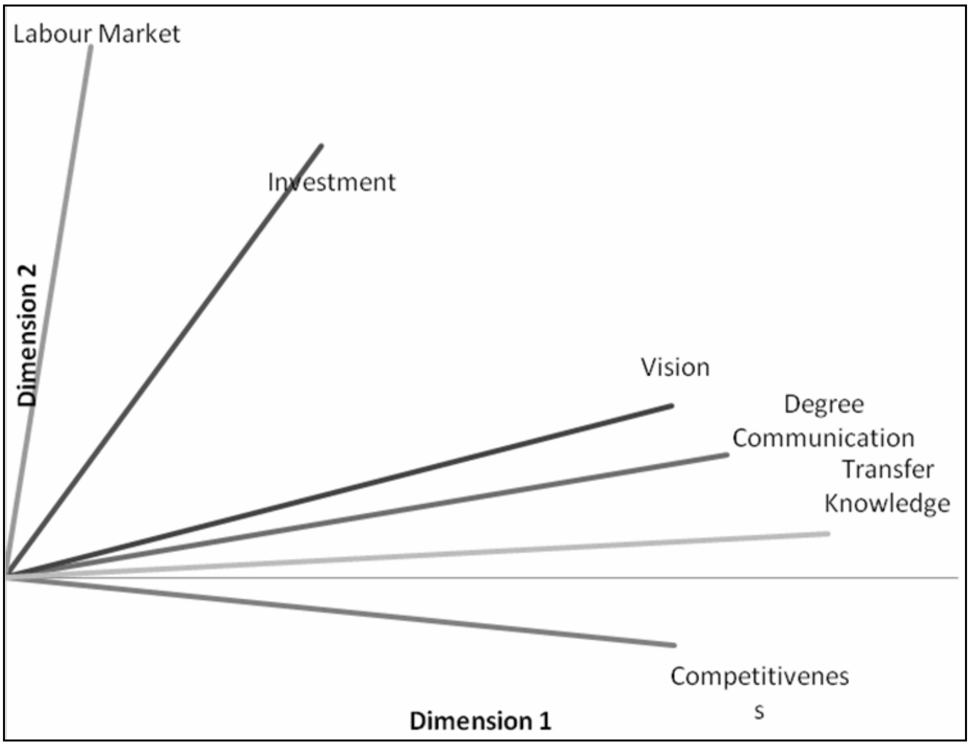
Figure 9 OA: biplot



It is interesting to observe that it is actually difficult to define similar groups observing the graphs as they are so dispersed but nonetheless a few clusters are definable. Two major groups are the ones defined along the governance dimension, on the negative side CNs with a main coordination objective can be found and conversely on the positive side CNs interested in cooperating among each other. In districts with a Leader firm or with a committee for the coordination of districts activities the coordination variables has a big influence in their differentiation. Other groups that have been found among the data indicate CNs with equally important SMEs and CNs in which at least a leading enterprise can be found.

The last component of the meta-model is the interaction with the environment in social and economics terms. The component loading is shown in Figure 10.

Figure 10 Interaction with socio economic environment: component plot



The variables 'investments' and 'labour market' can be projected onto Dimension 2, whilst the remaining variables, all the variables that discuss the knowledge factor of the CN, are positioned very close to Dimension 1 on the positive side. It is true that Investment is not exactly vertical, which means that a small part of Dimension 1 can also be explained by using this variable, but the predominant projection of it is on the vertical axis. Just like in the previous learning systems the interest at this point it to be able to name the dimensions according to the variables that lie on it.

The key word that describes the variables on the vertical axis is investment as there is an investment in R&D variable and an investment in labour market variable. Dimension 2 then can be called territorial investments. On the horizontal axis the main issues that are described are the knowledge factor, as all the variables indicate how much knowledge is being gained or transferred or, in any case, produced and used. So the horizontal axis can be called knowledge factor.

Each CN is characterised by two values which identify it relatively to the two dimensions found in the previous steps. A more functional way to see this result is by using the component plot (Figure 10) visualising the old variables in the new space defined by the principal components and the biplot (Figure 11) on which both the variables and the objects are shown. To summarise the PCA results in terms of variables reduction, in Table 5, for each meta-model element, the two orthogonal variables are listed.

To understand how each learning system conditioned the CN, every cluster was analysed observing each learning type separately.

Figure 11 Interaction with socio economic environment: biplot

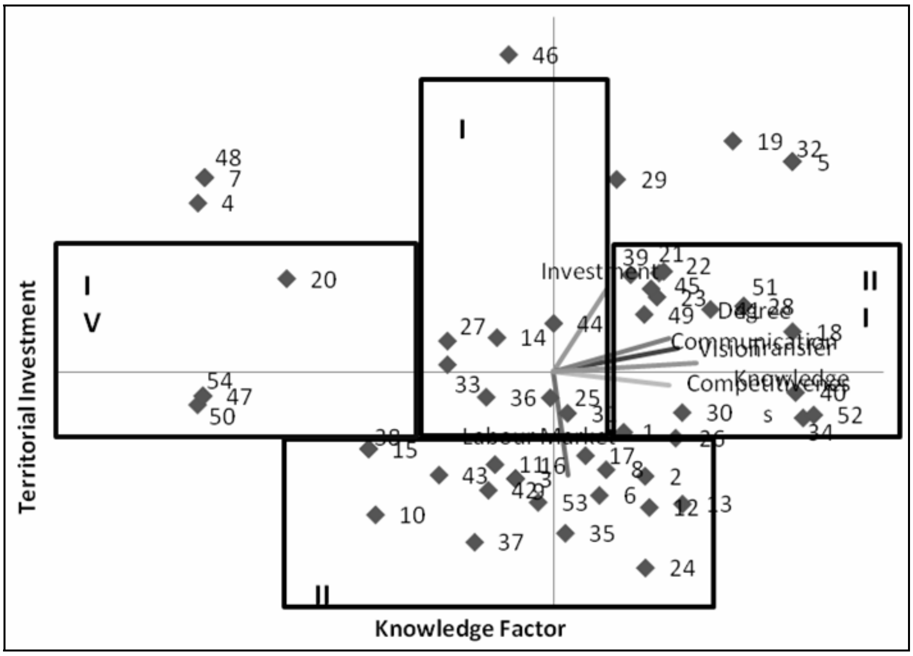


Table 5 Summary of dimensions names

	Dimension names	
	1	*2*
Operation structure	District dimension	District skills
Organisation arrangement	Governance	Leading to external
Interaction with socio economical environment	Knowledge factor	Territorial investment

The position of the CN is very scattered to show that there are major differences between the CNs on the collective learning scale.

The larger amounts of objects are positioned either close to the knowledge factor or around the investment in the labour market. This is understandable as in short term the production coefficients have to be considered fixed and so the large monetary investments in research and development are not as common as investing in knowledge factors and in the local labour market.

5 SWOT analysis and conclusions

SWOT Analysis, is a strategic planning tool used to evaluate the Strengths, Weaknesses, Opportunities, and Threats involved in a project or in a business venture. It involves specifying the objective of the business venture or project and identifying the internal and external factors that are favourable and unfavourable to achieving that objective. The technique is credited to Albert Humphrey, who led a research project at Stanford University in the 1960s and 1970s.

Table 6 Modified SWOT analysis

Selected industrial network	*(Strength/weakness)*			*(Opportunities/threats)*		
	District dimension	*District skills*	*Knowledge factor*	*Territorial investment*	*Governance*	*Export*
Maniago	Multi-stage SC 200 SMEs		Low	Very high	Political committee (PC) + Support agency (SA)	63%
Chair District	Multi-stage SC 1,200 SMEs		Low	High		
Suzzara	Two-stage SC 3,500 SMEs	Medium	Medium	Very high	PC	10%
Porphyry District, Cembra	SC 150 SMEs	Medium	Medium	Very high	SA	40%
RPD-Tech	Ten large companies	High	Medium	Very high		50%
Wine District of Canelli	51 enterprises	Medium	Medium	High	SA	40%
Automotive District Stuttgart	Multi-agent	High	High	Very high		70%
Canavese ID	Scientific park	High	Medium	Very high	SA	64%
EMC2	Scientific park 1,400 SMEs	Very high	Very high	High		50%
Shoes District of Verona	Flexible SC 524 SMEs	Low	Low	Low	SA	60%
BIO Cluster District – bioindustry park	Scientific park 344 companies	High	High	Low	Regional system integrator	
Evonet	Flexible SC six SMEs	Medium	Medium	Low	Managerial center (MC)	
Joinex	SME association 11 companied	Low	Low	None	MC	0%
Loire Numerique	Development agency 90 SMEs	Medium	Medium	Very high		40%
Club GIER	Development agency 120 SMEs	High	High	High		40%
The industrial symbiosis	Network five SMEs		High	Medium		

Table 6 Modified SWOT analysis (continued)

Selected industrial network	*(Strength/weakness)*			*(Opportunities/threats)*		
	District dimension	*District skills*	*Knowledge factor*	*Territorial investment*	*Governance*	*Export*
Walbrzich Special Economic Zone "Invest Park" Ltd.	Scientific park 65 SMEs	High		High	SA	0%
Scientific park 55 SMEs	High	Medium	High	Cooperation with banks and joint-stock company		

The method is applied here in a modified version in order to exploit the potentiality of collaboration inside networks. Now strength and weakness factors refer to the intrinsic organisation of the network as a whole, depending on its OA and OS. Opportunities and threats in present work are not referring to an external market but to the socio-economic context which the network is placed in. The resulting modified SWOT analysis is presented in Table 6. Only a reduced set of industrial networks is displayed for sake of clarity. The networks have been chosen in order to cover the widest spectrum of typologies and of interested countries.

Owing to the three blocks meta-model at the basis of present analysis, the PCA has been applied three times to three different subset of variables. In all the three instances of the PCA application two orthogonal dimensions have been found as the best compromise, according to the Kaiser criterion. This leads to a global number of six dimensions that have been used as parameters in the SWOT analysis. Obviously the PCA allows only to identify the number of dimensions and the variables that are more correlated with every dimension, not the name of the dimensions. The name assigned to each dimension has been chosen using common sense and trying to make reference to the correlated variables.

The parameters have been divided in internal parameters: referring to the analysis of the internal organisation of the network and external parameters, referring to the socio-economic environment hosting the network. Despite the origin of the six criteria, the dimension named 'territorial investment' is halfway between external and internal and has been considered in the analysis as an external factor.

Differently from the original SWOT analysis, present analysis allows an easy and simultaneous comparison among all the networks analysed.

The resulting Table 6 allows to detect the opportunities of collaboration in every networks. As an example the Canelli Industrial District of the wine is a network vertically organised and it is characterised by strong links between a few leader enterprises and a large amount of small agricultural enterprises (less than ten employees). Nevertheless present level of automation and of mechanisation allows also the SMEs to be involved in almost any production phases. The internal characteristics of the District are a large number of micro enterprises (with less than ten employees) with low skills – a threat to the stability of the network – and a substantial number of small and medium enterprises (SME) with high level of knowledge and organisation that represents a strength point of the network. Because of the importance of the territory in the production, the relationships between firms and the socio-economical environment are very high and represents an important opportunity for the district growth.

The research shows how industrial networks are more than just economic entities, but can be considered a socio and cultural dynamic entity. The initial research brought to life three processes through which CN, or actually any agglomeration of institutions, collaboration can be described. The more traditional system is the one through which SMEs specialise in the work they do, which has a main recognition in the skills and functions adopted. Another learning system was then found, through a localisation process. This was found by analysing how the network is formed. Three possible types of characters were found, one for each dimension, starting with the governance type, moving then to the type of CN under analysis and finally if there are leading strengths. The last but nonetheless important learning system was the collective learning, which is the more social and maybe modern approach to knowledge distribution among the SMEs of the network. By combining all the results into one large summarising table, it is possible to see exactly how each CN is defined along the three learning systems. In this way it is possible to understand how the CNs behave and also recognise in what direction the ID should move to improve and innovate certain factors.

The final step of each learning system analysis is therefore to cluster the IDs in order to recognise shared issues and to better exploit the common strong points.

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