# Social Network Analysis of Country Participation in Horizon 2020 Programme

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***Abstract****. Social network analysis has had multiple application through a variety of disciplines. This paper examines various examples of applying social network analysis and covers background of the theory. Main purpose of the paper is to use social network analysis to analyze country participation in the Horizon 2020 programme, mainly using measures of centrality. Few countries have emerged as central, and additional characteristics of those countries, like funding and beneficiaries have been evaluated. The importance of understanding formed relationships in Horizon 2020 lies in strategic decision making on partnerships, projects, and funding.*

**Keywords.** Social network analysis, Horizon 2020, graph theory

## 1 Introduction

Social network analysis (*SNA*) is "commonly used for mapping and measuring relationships and information flows among people, groups, organizations, computers, websites and other information/ knowledge processing entities" (Vrček, et al., 2013). The links between the nodes represent connections, while nodes itself can be, as stated, people, groups or other entities. (Freeman, 1984) in (Wasserman & Faust, 2009) states "the methods of social network analysis provide formal statements about social properties and processes".

The point of SNA is not only to map and measure relationships between the nodes, it is also to understand the structure of a network and to draw conclusions that can support research on the impact of the relationship on an actor. (Grunspan, et al., 2014) are for example stating that "SNA aims to understand the determinants, structures, and consequences of relationships between actors". Although the relationships SNA analyses are most often those between human beings, links among groups or organizations, as well as those among nation-states or international alliances are also examined (Freeman, 2004). Having that in mind, it is no wonder that multiple applications of SNA are discovered in literature review: (Grunspan, et al., 2014) studied social interactions between students in undergraduate education and their impact on learning outcomes, (Putnik, et al., 2016) applied the concept of social networks through an altered education process and found that the quality of students' work was better when students were between the interaction paths of other students.

Various other applications of SNA include examining and modelling social interactions between animals (Coleing, 2009), analysing team sports through SNA (Lusher, et al., 2010), as well as exploring the influence of social networks on innovation (Lewrick, et al., 2007) and understanding interactions between health professionals (Pow, et al., 2011). (Eveland Jr & Kleinman, 2013) used SNA to compare general and political discussion networks within voluntary organizations and (Johnson, et al., 2008) have explored how a network position of a non-profit organization affects its capacity level. (Chung & Paredes, 2015) have implemented SNA in analysing social learning to find that the learning is influenced by social network properties.

For the purpose of this article, connection between social network analysis and project management is interesting. Example of this kind of connection is the research of (Mohan & Paila, 2013) in which SNA was used as a visual tool to help with effectively managing stakeholders on projects. Further on, (Fitsilis, et al., 2009) have applied SNA in improving software project control with the goal of "enabling better team selection and SNA being the tool for managing project risk and improving project time and cost management". Research similar to the one in this paper was conducted by (Divjak, et al., 2010) where structure of project partnership in Eureka network was analysed using SNA. There are three main findings of that research: "countries from the same region cooperate more, country's level of development does not guarantee central position in the network, and bilateral partnerships are the most successful ones".

The purpose of this paper is to connect SNA as a powerful tool for analysing relationships in a network and the Horizon 2020 programme as the main EU framework programme for research and innovation. Horizon 2020 was announced in 2011 after evaluating existing and past programmes on the EU level. It is an 80 billion euro programme that was developed to boost research, innovation and competitiveness in Europe (European Commission, 2011). The funding is available from 2014 to 2020 and with the political backing, has the goal to "ensure Europe produces world-class science, removes barriers to innovation and makes it easier for the public and private sectors to work together in delivering innovation" (European Commission, n.d.). There are multiple programme sections within Horizon 2020, largest three being excellent science, industrial leadership, and societal challenges, each with specific elements. Legal entities of different kind can participate in Horizon 2020, such as universities, small and medium-sized enterprises (SMEs), large companies, research organizations, non-governmental organizations (NGOs). In Horizon 2020, bi-annual work programmes cover funding opportunities and current one is built for 2016-2017.

There are multiple applications of the provided data on Horizon 2020, such as visualization on coordinating projects, funds, and project count (Passas, 2016). The European Union Open Data Portal itself is listing applications of the open data in general, similar to the one above, but with a disclaimer that third party applications are not controlled (European Union Open Data Portal, n.d.), which is why it is important to extract relevant Horizon 2020 data directly from the European Union Open Data Portal. Using SNA is not uncommon in analyzing EU projects results and formed networks. (European Commission, 2015) has published a report on results of 7th Framework Program (FP7) participation in which "effects and outcomes of networking at the macro level" were analyzed through network analysis and at the micro level through case studies, in-depth interviews and a survey. The SNA aimed to "provide a broad view of networking activities that took place in FP7 and its different specific programmes and underlying thematic areas". Some of the findings included that 86% of collaboration pairs from Framework Programme 6 were not renewed in FP7, as well as that Universities and research organisations "derive an advantage from being centrally located in the co-participation network of framework programmes".

Based on previous research and research interests, the following research questions for this paper have been defined, that ought to be answered through the social network analysis and through available data.

RQ1: Based on centrality measures, do the largest member state countries hold central position in the network?

RQ2: Have the countries with the highest centrality measures received most funding to date via Horizon 2020 projects and do those countries have the highest success rate of applied projects?

RQ3: Among the countries with highest centrality measures, what type of institutions are the top beneficiaries?

The research findings can be of value to organizations planning to participate in Horizon 2020 projects, as well as to public in general, to gain a holistic overview of the roles of member countries in Horizon 2020 projects to this date. The paper is organized as follows: first, an overview of social network analysis is provided, as well as the connection between SNA and graph theory. After, the research method and results are presented, and finally the answers to research questions are provided, and conclusion is laid out.

# 2 Social network analysis method

If SNA determines and analyses relationships within actors in a network, it is important to define what a "network" is, and how the network theory is related to one of its foundations, graph theory.

(Wasserman & Faust, 2009) state that there are "three mathematical foundations of network methods: graph theory, statistical and probability theory, and algebraic methods". Also according to (Wasserman & Faust, 2009), graph theoretic, sociometric, and algebraic schemes can be adapted to represent a wide range of network data. Relevant for this paper, sociometric notation presents the relationship data in a sociomatrix, where "the rows and columns refer to the actors making up the pairs" and the sociomatrices are essentially adjacency matrices for graphs. Meanwhile, according to the same authors, graph theoretic notation is "useful for centrality and prestige methods, cohesive subgroup ideas, as well as dyadic and triadic methods".

There are different ways networks can be categorized. First, networks can be unipartite or one-mode (consist of only one type of actor), or bipartite or two-mode in which actors are linked with the groups to which they belong (Grunspan, et al., 2014). An example of a bipartite network is connecting universities to projects they participated on, while a unipartite network would connect universities to universities. Networks can also be studied from an ego-centered and socio-centered approach. Socio-centered approach is focused on the characteristics of the network as a whole, while ego-centered approach focuses on an actor in a network and is analyzing its immediate relationships.

Definition of a social network deriving from graph theory conceptualizes social network as a graph: there is a set of vertices as social actors and a set of lines representing social relations between these vertices (nodes) (de Nooy, 2008).

Same author states that social network is more than a simple graph as it covers details on social actors, as well as the nature of the relationships between the nodes. Depending on the nature of ties in a graph, it can be undirected and directed. In undirected graph, sets of nodes are not ordered pairs, while in a directed graph the pair of nodes is ordered and there is an associated direction between nodes. Example of an undirected graph is a student A studying with student B, and an example of a directed graph is student A's perception of student B as being smart (not necessarily mutual) (Grunspan, et al., 2014).

As stated, networks have developed from several foundations, one of which, often used to describe networks, is graph theory. (Brandes, et al., 2016) define elements of graphs, since it is assumed networks are represented as graphs: "an (undirected) graph $G=(V,E)$ consists of a set V of vertices (also called nodes) representing actors and a set of (undirected) edges (also called links) representing ties between actors. An edge is thus an unordered pair of vertices representing a symmetric relationship. If there exists an edge $e=\{u,v\}\in E$, we say that $u$ and $v$ are adjacent and that $u$ and $v$ are incident to e. We will use $n=|V|$ for the number of vertices and $m=|E|$ for the number of edges of a graph.

Some of the centrality measures analyzed in this paper are degree centrality, betweenness centrality, and closeness centrality. Centrality measures serve as indicators of important nodes in a network.

### 2.1. Degree centrality

Degree of a node is "the count of the number of ties to other actors in the network, i.e. the number of lines that are incident with it" (Divjak, et al., 2010). (Wasserman & Faust, 2009) state that this measure focuses on the most visible actors in the network (…). An actor with a large degree is in direct contact or is adjacent to many more actors".

Degree centrality formula, from (Divjak, et al., 2010):

$$C_D(n_i)=d(n_i)=\sum_{\forall j\neq i} x_{ij} \tag{1}$$

Where:
$C_D$ $(n_i)$ = degree centrality of actor $i$
$d$ $(n_i)$ =degree of node $i$
$x_{ij}$ = 1 if $I$ is incident to $j$; 0 if $i$ is not incident to $j$
$n$ = number of nodes in the network

### 2.2. Betweenness centrality

(Wasserman & Faust, 2009) state that "the important idea with betweenness is that an actor is central if it lies between other actors on their geodesics". This means that an actor must be between many of the actors to have a large "betweenness" centrality.

Betweenness centrality formula, from (Divjak, et al., 2010):

$$C_B(n_i)=\frac{\sum_{j<k,i\neq j,i\neq k}\frac{g_{jk}(n_i)}{g_{jk}}}{\frac{((n-2)(n-1))}{2}} \tag{2}$$

Where:
$C_B$ $(n_i)$ = standardized betweenness centrality of node $i$
$g_{jk}$ $(n_i)$ = number of geodesic linking $j$ and $k$ that contains $i$ in between
$g_{jk}$ = total number of geodesic linking $j$ and $k$

### 2.3. Closeness centrality

"Closeness focuses on how close an actor is to all the other actors in the set of actors; the idea is that an actor is central if it can quickly interact with all others" (Wasserman & Faust, 2009).

Closeness centrality formula, from (Divjak, et al., 2010):

$$C_C(n_i)=\frac{n-1}{\left(\sum_{j=1,i\neq j}^{n} d(n_i,n_j)\right)} \tag{3}$$

Where:
$C_C$ $(n_i)$ = standardized closeness centrality of node $i$
$d$ $(n_i,n_j)$ = geodesic between $i$ and $j$

## 3 Research

### 3.1. Research method

The research in this paper covered all EU research projects under Horizon 2020 (2014-2020), with the goal of building a social network and answering the research questions. The dataset containing projects was downloaded from the European Union Open Data portal on March 21st 2017. CORDIS datasets are produced on a monthly basis and on the date of download, there have been 13776 downloads. For each participant Cordis record number (RCN), ID, Acronym, Role, Organisation Name, Organisation Short Name, Organisation Type, Participation Ended, EC Contribution, and Organisation Country have been listed in the dataset (European Union Open Data Portal, 2016). Data has been analysed using RStudio, a tool based on R, a free software environment for statistical computing and graphics (The R Foundation, n.d.). RStudio was chosen for data analysis in this research as it supports a variety of techniques, it is well supported by packages developed for social network analysis, and it provides an environment for both analysis and visualization of the generated networks.

In RStudio, XLConnect, readxl, sna, and igraph packages were used to import and analyse dataset.

The package “sna” serves as a tool to obtain centrality degrees laid out earlier in this paper. The following steps were taken to import and analyse data:

Import dataset:

```
Horizon <- read_excel (“path”)
```

Check the structure of the imported dataset:

```
str(Horizon)
```

Create matrix containing information on countries and projects:

```
Y <- as.matrix
(table(Horizon$country,Horizon$projectI
D))
```

Create adjacency $n \times n$ matrix A, where $n$ is the number of vertices in the graph (number of participating countries):

```
A <- Y%*%t(Y)
```

Create a graph out of the created matrix:

```
Horizon.graph <- graph.adjacency (A)
```

Plot the created graph with particular, defined look:

```
plot (Horizon.graph1,
vertex.size=degree(Horizon.graph1)/30,
edge.color="light grey",
vertex.color="grey",
vertex.frame.color="grey",
vertex.label.cex=0.8)
```

In total, 131 countries centrality measures have been analysed and made it to the graph, as the research covered all country participants. To obtain good results, only basic data covering country, project ID, city, and project name remained in the sheet.

To answer the research questions, information gathered through SNA was combined and enriched with other analysis provided by European Commission on the current status of Horizon 2020 projects and countries’ participation.

## 3.2. Research findings

The created social network where nodes represent countries and edges represent partnerships on projects was the basis to perform further analysis on the position of countries, through centrality measures. If this network is perceived as a graph, the graph is simple, undirected, and unipartite. The graph presents all countries that participated in the Horizon 2020 programme. It is visible on Figure 1 that countries with high centrality degrees are located in the centre of the network, maintaining a number of relations with other countries. Similarly, countries with smaller centrality degrees are located on the outskirts of the graph, as they are not as connected as the central countries.

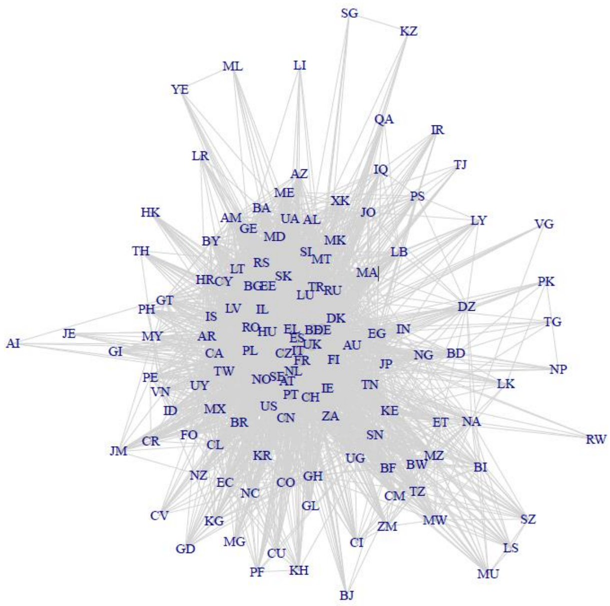

**Figure 1.** Social Network Analysis Graph

Degree centrality measures are laid out in Table 1, sorted from largest, showing top five countries with the largest degree centrality, which are United Kingdom, Germany, France, Italy, and Belgium.

**Table 1.** Degree centrality

| Country | Degree centrality |
|---|---|
| United Kingdom (UK) | 123 |
| Germany (DE) | 122 |
| France (FR) | 113 |
| Italy (IT) | 113 |
| Belgium (BE) | 111 |

These actors should begin to be recognized by others as a major channel or relational information (Wasserman & Faust, 2009). According to a similar research, conducted by (Divjak, et al., 2010), degree centrality is an indicator of “a country’s activity in a network” and the countries with a higher degree centrality should be perceived as an attractive partner.

Table 2 shows top five countries in regards to betweenness centrality, which are the same as above: United Kingdom, Germany, France, Italy, and Belgium.

**Table 2.** Betweenness centrality

| Country | Betweenness centrality |
|---|---|
| United Kingdom (UK) | 566.487 |
| Germany (DE) | 562.704 |
| France (FR) | 341.199 |
| Italy (IT) | 345.845 |
| Belgium (BE) | 349.307 |

As mentioned, betweenness centrality is determined by the node being between other actors in a network. In this research, these are the countries that have the highest betweeneess centrality meaning they control the flows between actors in the network.

Table 3 shows countries with highest closeness centrality, which is recorded for the same set of countries: UK, Germany, France, Italy, and Belgium.

**Table 3.** Closeness centrality

| Country | Closeness centrality |
|---|---|
| United Kingdom (UK) | 0.007299 |
| Germany (DE) | 0.007246 |
| France (FR) | 0.006807 |
| Italy (IT) | 0.006803 |
| Belgium (BE) | 0.006711 |

For these countries it is easiest to access other actors within the network, meaning they can build contacts fast.
Looking at the positions in the network, it is interesting to look at centrality degrees of recent European Union members and how these countries have positioned themselves in this network. Table 4 shows countries that most recently joined EU and their centrality measures.

**Table 4.** Newest EU members and degree centrality measures

| Country | Degree centrality | Betweenness centrality | Closeness centrality |
|---|---|---|---|
| Croatia | 63 | 23.767 | 0.005076 |
| Romania | 74 | 42.546 | 0.005376 |
| Bulgaria | 68 | 30.921 | 0.005208 |

The table above shows that Romania and Bulgaria do have higher centrality measures than Croatia, which does make sense since the countries have entered the EU six years earlier than Croatia. It would be an interesting point to follow throughout time, to see whether Croatia will be earning a more central place as the time progresses.

The research questions have been answered.

RQ1: Based on centrality measures, do the largest member state countries hold central position in the network?

Four out of five most central countries in the centrality measures analysis are in the top five largest member states, based on population. Those countries are (in order from the most populated one); Germany, France, United Kingdom, Italy (eurostat, 2017). Belgium is the 9$^{th}$ most populated country in the EU, but is in the top five countries in our analysis, while on the other hand Spain is the 5$^{th}$ most populated country in the EU but has not made it to the top five most central countries in Horizon 2020.

RQ2: Have the countries with the highest centrality measures received most funding to date via Horizon 2020 projects and do those countries have the highest success rate of applied projects?

**Table 5.** Success rate and funding to date in Horizon 2020. Data from (European Commission, 2016)

| Country | Funding to date (in million Euro) | Success rate |
|---|---|---|
| United Kingdom | € 2.634,93 | 14,8% |
| Germany | € 3.031,00 | 15,7% |
| France | € 1.758,66 | 16,8% |
| Italy | € 1.413,62 | 11,6% |
| Belgium | € 808,42 | 17,1% |
| Ireland | € 303,44 | 15,3% |
| Portugal | € 286,89 | 12,4% |
| Spain | € 1.509,16 | 13,3% |
| Netherlands | € 1.329,18 | 16,1% |
| Luxembourg | € 43,19 | 16,0% |
| Denmark | € 425,73 | 15,0% |
| Sweden | € 571,18 | 13,2% |
| Czech Republic | € 106,73 | 13,2% |
| Austria | € 491,51 | 16,3% |
| Slovenia | € 94,48 | 10,0% |
| Croatia | € 28,83 | 10,8% |
| Poland | € 153,70 | 11,1% |
| Slovakia | € 43,84 | 13,7% |
| Hungary | € 94,51 | 10,0% |
| Finland | € 350,07 | 12,9% |
| Estonia | € 60,36 | 13,2% |
| Latvia | € 19,42 | 11,4% |
| Lithuania | € 18,82 | 11,3% |
| Romania | € 66,25 | 11,4% |
| Bulgaria | € 23,05 | 9,5% |
| Greece | € 351,13 | 12,1% |
| Cyprus | € 51,69 | 9,1% |

It appears that countries with highest centrality measures do have high received funding. UK, Germany, and France in general have received most funding to date through Horizon 2020 projects. However, Spain and Netherlands show high received funding, higher than Italy and Belgium, although their centrality measures are not as high. When analysing success rates, based on Table 5, the highest one is the one of Belgium, followed by France, Austria, Netherlands and Luxembourg. This demonstrates that having high centrality measures (degree, betweenness, and closeness) is not necessarily an indicator of a success rate. Interestingly, Belgium was found to be quite central in SNA, although funding received is not as high, but its success rate is the highest among the member states (17.1%). UK on the other hand, has a success rate of 14.8%, but is the most central node in the network, based on the SNA and has received most funding to date. Further deeper statistical analysis is needed to determine the exact effect of these indicators.

RQ3: Among the countries with highest centrality measures, what type of institutions are the top beneficiaries?

Analysing the top 10 beneficiaries (based on financial distribution) for top 5 countries based on the SNA, the results show that institutes/research organizations and universities are main beneficiaries in these member states

- UK: all top 10 beneficiaries are universities
- Germany: 6 institutes/research organizations, 4 universities
- France: 7 institutes/research organizations, 2 universities
- Italy: 5 institutes/research organizations, 5 universities
- Belgium: 3 institutes/research organizations, 6 universities

## 4 Conclusion

Social network analysis is a powerful way to determine and analyse connections between actors in a network. Understanding the nature of formed relationships is important to make data driven decisions and to gain a holistic view of the partnerships within a network. In this research, SNA served as a foundation for determining central roles of countries in the Horizon 2020 network that resulted in answering key research questions. It can be concluded that the size of the country is somewhat related to high centrality measures. UK, Germany, France, and Italy hold highest measures of degree, betweenness, and closeness centrality. Spain, which is following these countries in size does not hold high centrality measures and Belgium has taken its spot in the top five countries based on centrality. This means that these five countries are the most central, control the flow of information and resources, and can form partnership easily. Further on, high participation of universities and research institutes was detected for the five most central countries in the network, and the success rate (although all top countries listed here do have above average success rate), as well as the funding received, do not seem to follow the centrality measures. Further research should be conducted to determine deeper connection and statistical significance of the statements here, which are based on the qualitative analysis. Some of the limitations of the research include the fact that the SNA has been performed on a whole set of data and the findings present only highest centrality countries, lack of further statistical analysis to connect other research elements to centrality measures (such as funding or beneficiaries). Further, a limitation is the up to date data source, as these sources are updated regularly on Cordis website, it also means that the network might be changing. Finally, additional network analysis measures should be deployed to analyse data further.

To conclude, SNA has demonstrated to be a good choice for determining the central positions in the network created by partnerships through the Horizon 2020 projects and the ideas for expanding this research have been laid out here as well.


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