E-CONOM

Online tudományos folyóirat
Online Scientific Journal

Tanulmányok a gazdaság- és társadalomtudományok területéről
Studies on the Economic and Social Sciences

ISSN 2063-644X

XII./1.

http://www.e-conom.hu

2023

E-CONOM

Online tudományos folyóirat I Online Scientific Journal

ISSN 2063-644X

DOI: 10.17836/EC.2023.1.066

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Social Network Analysis of Horizon 2020 Projects on Drones

In the course of the research, data on Horizon 2020 project participants with "drones" SciVoc identifiers (N = 2245) were downloaded from a database compiled from Scopus data tables (N = 2245). An algorithm was then used to plot the vectors of the project participants' contact pairs, which were then transformed into a graph and an adjacency matrix. From an intermediate, optimised graph, the network of connections was plotted. Network metrics were then computed, and then the clusters of the network were drawn, and some characteristics of the clusters were computed. SQL and R codes were used for the analysis.

Keywords: social network analysis, projects, drones, Horizon 2020
JEL Codes: C61, D85, O22

A Horizont 2020 drónkutatási projektjeinek kapcsolatháló-elemzése

A kutatás során a Scopus adattábláiból általunk összeállított adatbázisból letöltöttük a „drones" SciVoc-azonosítóval rendelkező Horizont 2020-projektrésztvételek adatait. (N = 2245) Ezután egy algoritmussal felírtuk a projektrésztvevők kapcsolatpárjainak vektorait, majd ezt gráffá és szomszédsági mátrixszá alakítottuk. Egy köztes, optimalizált gráfból felrajzoltuk a kapcsolathálót. Ezután hálózati mutatókat számoltunk ki, majd felrajzoltuk a háló klasztereit, s kiszámoltuk a klaszterek néhány jellemzőjét. Az elemzés során SQL- és R-kódokat használtunk.

Kulcsszavak: kapcsolatháló-elemzés, projektek, drónok, Horizont 2020
JEL-kódok: C61, D85, O22

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Introduction and Objectives

The paper gives an example of SNA (Social Network Analysis), a subfield of network research. The research will focus on calculating the main network indicators of Horizon 2020 projects related to drone research and mapping the clusters of the network. The results obtained will allow further analysis and comparisons in different segments.

This research is important because drone technology has come of age in recent years. In addition to initial military and recreational uses, the application of UAVs has become common in many fields. Emergency relief, archaeology, ecological diversity and environment conservation, security services, anti-crime and anti-terrorism operations, aerial surveillance, cinematography, media coverage, scientific research, surveying, cargo transport, mineral extraction, manufacturing, forestry, solar energy, thermal electricity, harbours, and agriculture are just a few examples. The complex technological needs and the internationalisation of areas of application highlight the need for international research cooperation in this field. Given that several countries (e.g. Hungary) have recently started to develop drones for multiple purposes, it is certainly worth examining what scientific cooperation is taking place at European level. An examination of research networks under Horizon 2020 provides perhaps the most general picture of the state of European cooperation and the extent to which the nature of the networks can provide a link for those just entering the field.

In addition to quantifying the main characteristics of the network, exploring the individual clusters and clarifying the „balance of power" within clusters can also be beneficial for new entrants and those wishing to develop their activities in the future.

Background Literature

The analysis of social networks has been a focus of academic interest since the second half of the 1990s, after a number of precedents (Barabási, 2003). However, network research was already an important field of science decades earlier, and we can consider its "coming of age" from around the second half of the 1950s. The network research methods used in this paper build on the results of the last decades. Models used: a model describing random networks (graphs) (Erdős & Rényi, 1960), a configuration model for networks with a fixed degree distribution but otherwise completely random connections (Bollobás, 1980; Molloy & Reed, 1995; Newman, 2010), a small-world model around the question "Are we at most six steps away from anyone?" (Watts & Strogatz, 1998), a model of scale-free networks (Barabási & Albert, 1999), and a Barabási-Albert model describing the formation of scale-free networks (Albert & Barabási, 2002).

SNA methods are used in the literature to examine both project results and the different characteristics of projects. One of the main uses of SNA methods is to analyse the effectiveness of innovations within projects. The topics covered are very diverse.

European project networks have been analysed by several authors from the perspective of innovative energy systems. Innovation systems adapt to funding program goals, modifying taxonomy, topology, and structural properties. Network properties, such as cohesion and centrality, explain efficiency and effectiveness, benefiting policymakers and entities (Calvo-Gallardo, Arranz, & de Arroyabe, 2022). Framework programmes address energy-related issues, but priorities shift over time, reflecting energy transition, examining transmission vs. distribution grid importance and collaboration patterns (Klitkou, Fevolden, & Andersen, 2022). It was found that e.g. FAIR data and tools support climate and energy transition decision-making and actions (Balest, Pezzutto, Giacovelli, & Wilczynski, 2022). Others looked at more general issues in energy innovation networks, such as how group choices differ from individual choices in various regions, cities, or countries in a network (Klöckner, 2019).

Agricultural and rural innovations are similarly important related topics based on the literature. Multi-actor partnerships in innovation networks of this area are primarily funded by European funds, with research entities and farmers as central actors. The network's heterogeneous composition and increased interaction between organizations contribute to its success (Guerrero-Ocampo, Díaz-Puente, & Espinoza, 2022). Innovation systems' effectiveness can depend on participant heterogeneity, geographic diversity, and network position (Fernandez de Arroyabe, Schumann, Sena, & Lucas, 2021). Rural projects' social innovation initiatives may strengthen relationships by altering existing social networks (Lombardi, et al., 2020). The role of local authorities in this type of projects is not negligible, as the SNA methodologies have shown (Yang, Chen, & Xu, 2020). Local food networks have high innovation potential, focusing on organic farming and food as a boundary object for shared visions and goals (Favilli, Rossi, & Brunori, 2015).

The above studies using SNA analyses seem to be of most interest from an organisational point of view. However, some studies are also relevant in terms of their subject matter and methodology, even if they are not necessarily directly related to UAVs.

Social network analysis may be used to determine whether there are any recurring themes in the study of information and communication innovations and diffusion linkages created by regions in networks funded by the European Union, as well as how differently these relationships relate to productivity (Vicente, Garciá-Muñiz, & Billón, 2020). The related approach can be used for the assessment of systemic risk of networks (Barucca, et al., 2020). Key actors, network vulnerabilities, paths for investigation, link and attribute weights may all be identified (Burcher, 2020). Regional competence to secure European financing and gain a central place in collaborative networks promotes technological variety in European regions. In FP7, strong network centrality in a research partnership network correlates with technical variety (Muscio, Ciffolilli, & Lopolito, 2022). The combination of a modularity index and an enhanced silhouette index to determine an ideal number of clusters, which may be combined with team similarity measurements as inputs to a spectral clustering method, should yield relevant findings (Yang, Yang, Browning, Jiang, & Yao, 2019). Some findings emphasize the recent decade's innovation trajectories in Europe and reaffirm the technological and geographical dominance of the top firms (Capone, 2014). The examination of how to create a heterogeneous manycore with self-adaptive capabilities is further illustrated with pertinent instances (Lemonnier & Millet, 2012). Building resilience appears to require the participation of social networks, improving community reaction capability, self-organization, learning and education, and encouraging an adaptive culture, among other things (Gourbesville, 2012). The ex-ante development and management of university-industry partnerships within R&D cooperation has been studied using SNA. Given the significance of the anticipated consequences and the high volatility of these connections, it is necessary to comprehend the foundations of effective cooperation (Pinheiro, Lucas, & Pinho, 2015). However, the different segments of innovation projects related to drones have been analysed rather sporadically. The few results do not really form a coherent whole.

The idea of urban drones in these researches appears to be a crucial topic. High aspirations and overwhelmingly favourable experiences are present. Project-based learning that integrates multiple disciplines appears to be a crucial tool for analysing the social environment The idea of urban drones appears to be a crucial topic. High aspirations and overwhelmingly favourable experiences are present. Project-based learning that integrates multiple disciplines appears to be a crucial tool for analysing the social environment (Jacques, Bissey, & Martin, 2016). The space is mapped in a real-world setting using several drones (Mendes, 2021). Network theory may find interest in a drone-based digital twin augmentation framework with reusable and adaptable components (To, et al., 2021). Law enforcement organizations may be given the ability to look into criminal activity on a global scale by using social network analysis tools in the field of unlawful activities (Park & Stamato, 2021).

The topic of this paper seems novel. The main reason is that, although there are research directions and methodologies to consider in the literature, there is little research history specifically in the field of drone research and European project cooperation. There is a gap in the literature, as European projects have been analysed with different segments using SNA tools, but not drone research collaborations. However, it is clear from the literature that their structure has complex implications for the context of subsequent research, for collaborations and for potential connections. The analysis of research networks and clusters can be used to draw such conclusions.

Applied methods

The research involved downloading data on Horizon 2020 project participants with a "drones" SciVoc identifier from a database we compiled from Scopus data tables (N = 2245). Then, some network indicators were calculated.

Density the proportion of all possible contacts that were established. Density in an undirected graph can be written as follows:

$$D = \frac{2E}{N(N-1)} \tag{1}$$

, where E is the number of edges.

If all possible connections exist, i.e. everyone is connected to everyone else, then the density is 1. With a density value of 0, no one is connected to anyone. The density value is therefore a number between 0 and 1, with higher values reflecting a higher network density (Molnár, 2020).

Transitivity is the average probability that if a node is connected to another node, and that node is connected to a third node, then our initial node is also connected to the third node (Kisfalusi, 2018). Transitivity is also known as the average clustering coefficient (Barabási, 2017).

Clustering coefficient of the i-th node with degree k_i:

$$C_i = \frac{2L_i}{k_i(k_i-1)} \tag{2}$$

, where L_i is the number of links between the k_i neighbours of the i-th point. Its value is always between 0 and 1.

Average clustering coefficient for the whole network:

$$\langle C \rangle = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{3}$$

The diameter is the "path length" of the network: the maximum number of steps needed to get from one node to any other node by the shortest possible route. Networks with a small diameter are called "small world" (Barabási, 2006).

Starting from an average degree random network, the number of nodes that are further than d from the starting point:

$$N(d) \approx 1 + \langle k \rangle + \langle k \rangle^2 + \cdots + \langle k \rangle^d = \frac{\langle k \rangle^{d+1} - 1}{\langle k \rangle - 1} \tag{4}$$

, where $\langle k \rangle$ is the average degree.

$N(d)$ cannot be greater than N (the total number of nodes), so the distance cannot take any arbitrary value. For the maximum distance (d_{max}), and the number of elements in the network diameter, it is true that:

$$N(d_{max}) \approx N \tag{5}$$

If $\langle k \rangle \gg 1$, then both the numerator and denominator of equation (4) can be omitted from „-1":

$$\langle k \rangle^{d_{max}} \approx N \tag{6}$$

Therefore, the diameter of the network is:

$$d_{max} \approx \frac{\ln N}{\ln\langle k \rangle} \tag{7}$$

Based on a node-level centrality metric, centralization is a general method for estimating a graph's level of centrality. The equation is as follows.

$$C(G) = \sum_{v} (max_w\, c_w - c_v) \tag{8}$$

, where c_v denotes the vertex v's centrality.

The maximum theoretical score for a network with the same number of vertices, using the same parameters, such as directedness, whether we consider loop edges, etc., can be divided by to normalize the graph-level centralization metric. The most concentrated structure for degree, closeness, and betweenness is a star graph, whether it be an in-star, out-star, or undirected star.

Betweenness is a measure of how critical the network location of an actor is for network cooperation and information flow. If a node lies on many paths that are minimal routes between two other actors, it is likely to play an important role in the network (Kürtösi, 2011; Freeman, 1977).

Betweenness for v node:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{9}$$

, where σ_{st} is the number of shortest paths between nodes s and t, and $\sigma_{st}(v)$ is the number of paths through v of these nodes.

The normalized form is often used, where the expression (9) is (for undirected graphs) divided by $(N-1)(N-2)/2$.

The following expression is also often used as a normalised form:

$$normal\big(g(v)\big) = \frac{g(v) - min(v)}{max(v) - min(v)} \tag{10}$$

In both cases the value falls within the range $[0,1]$.

The graph with a single edge is the most centralized structure for eigenvector centrality (and potentially many isolates). The mean inverse distance to all other vertices is a vertex's harmonic centrality. An inaccessible vertex is thought to have an inverse distance of zero.

The mapping of clusters in a network is almost a discipline in its own right and can be limited to the most relevant methods for the analysis. The algorithm used divides the network into smaller and smaller parts until it finds the elements that serve as a bridge between each group, since they have a high value of the betweenness (9). Although the authors of the technical documentation (The igraph core team, 2003-2020) clearly refer to the mathematical-statistical basis of the algorithm (Newman & Girvan, 2004), equations (9)(10) in the referenced work are primarily used to delimit the clusters within the complex algorithm.

Based on the betweenness, we have also listed the main project participants. We have also analysed the participants in the cluster with the largest number of elements.

Results

The mapped network of connections alone says little about the nature of the network. What can be said is that there are peripheral groups and participants (institutions, firms, research organisations) in the sample, although not very many (*Figure 1*).

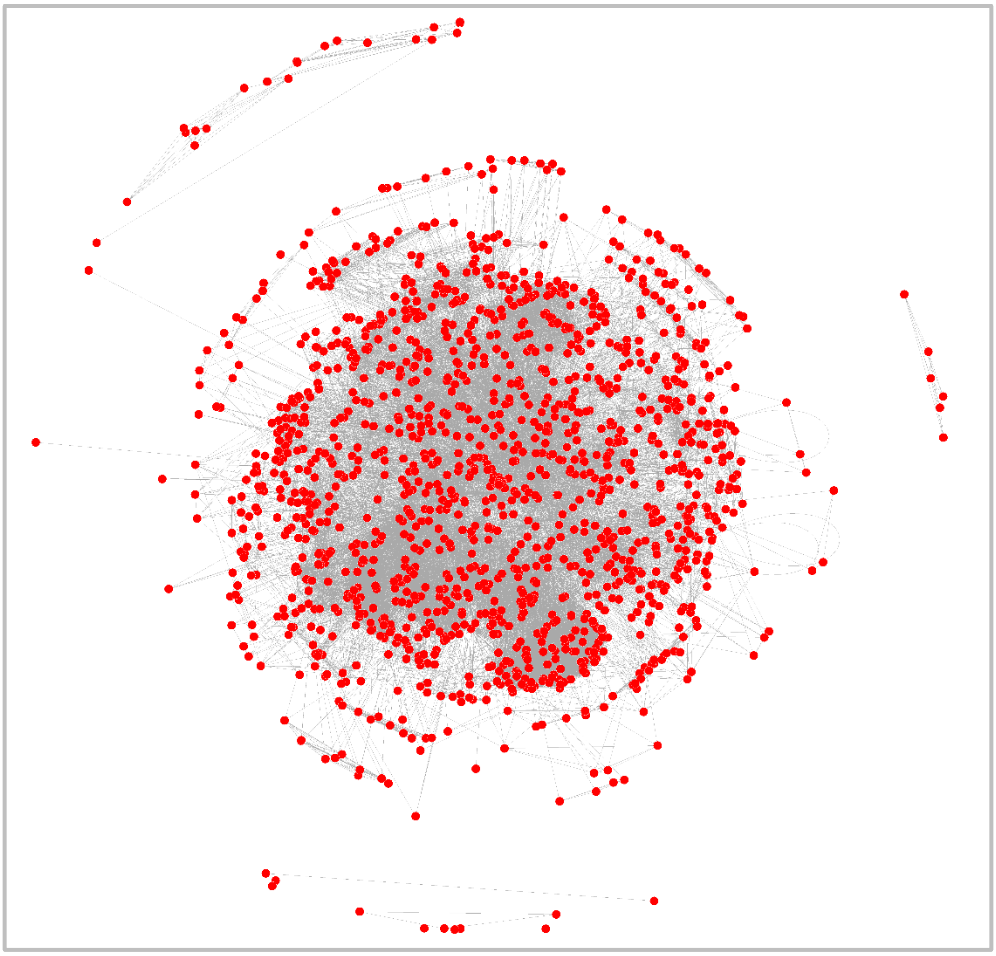

Figure 1. Project network
Source: own calculation

The network seems to be quite interconnected. However, the visual impression is often misleading. Especially in the case of relatively large networks, where the drawn edges and the mass of nodes essentially hide the structure of the network.

Table 1. Network indicators

Indicator	Value	Indicator	Value
Density	0.023	***Eigenvalue***	117.177
Transitivity	0.705	***Mean of harmonic centrality***	500.757
Diameter	5	***Rcn of max. betweenness***	1907101
Degree centrality (normalized)	0.192	***Number of clusters***	89
Mean of closeness centrality	0.016	***Elements of biggest cluster***	122

Source: own calculation

The *Table 1* indicates that, despite the relatively low density, the network is quite interconnected according to our visual impressions, as shown by the low diameter and high transitivity.

Although statistical testing of the distributions is beyond the scope of this paper, it can be stated with a fair degree of certainty that the network degree numbers do not follow a notable distribution, but such effects may nevertheless be present (*Figure 2*).

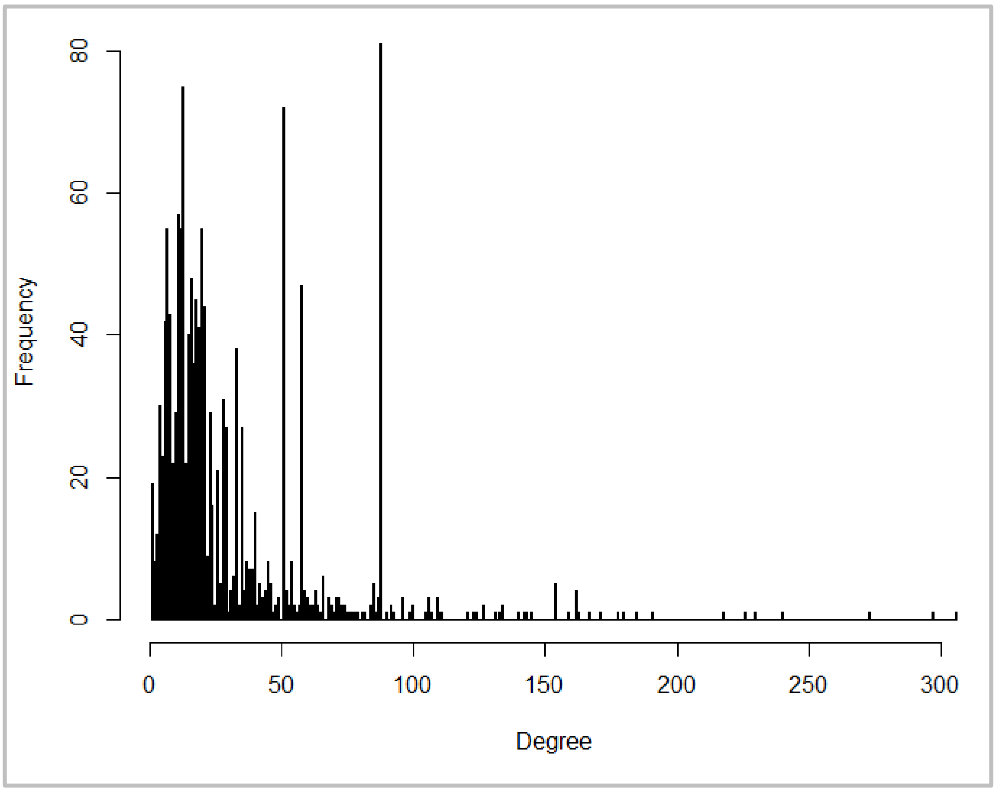

Figure 2. Frequency of degrees
Source: own calculation

Table 2. Ten most important participants by betweenness

Name (abbr.)	Country	Betweenness
CERTH	Greece	138422.56
CEA	France	94047.71
CNRS	France	90322.47
FHG	Germany	86788.60
DLR	Germany	58399.67
TU Delft	Netherlands	43049.19
EUROCONTROL	Belgium	41440.92
DTU	Denmark	28936.06
FADA-CATEC	Spain	27165.41
NLR	Netherlands	25318.52

Source: own calculation

The most important project participant for the network in *Table 2* may come as some surprise, as it is Greece.

The algorithm used has separated a very large number of clusters, and the number of elements in the largest cluster is also very high.

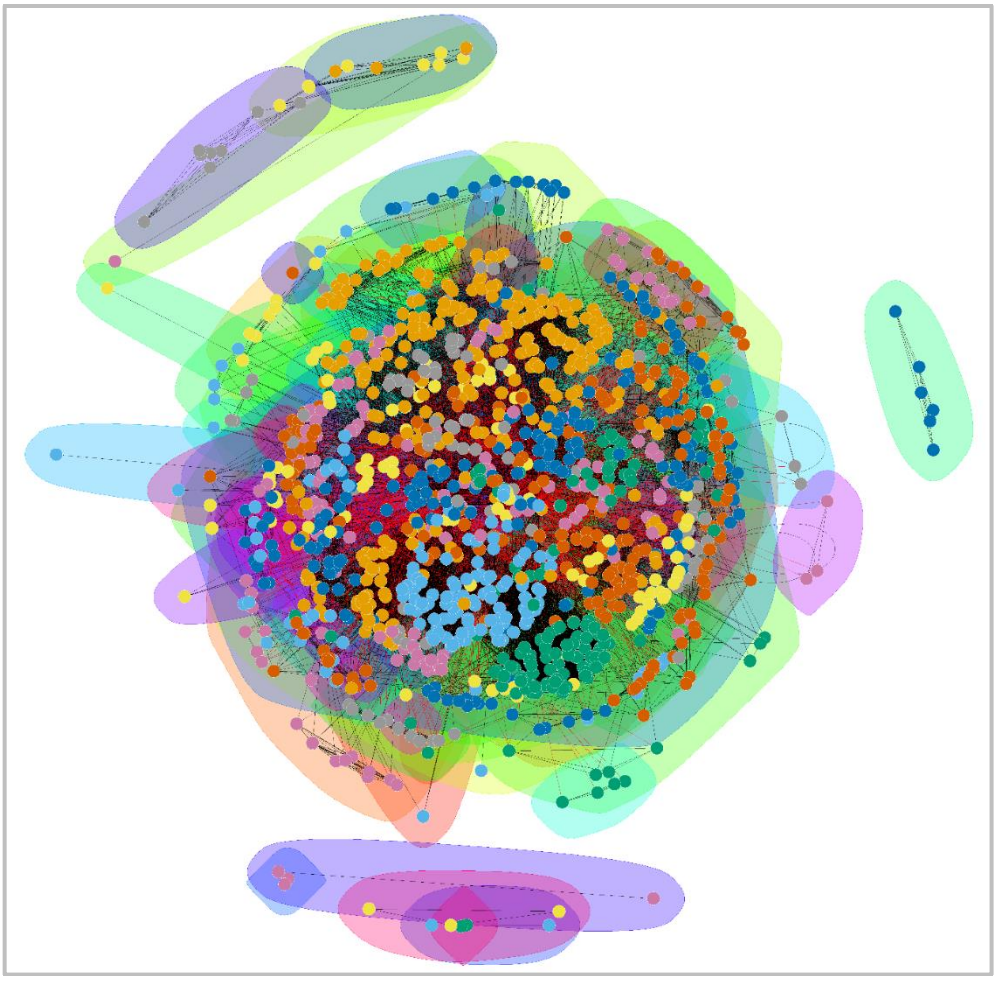

Figure 3. Project clusters
Source: own calculation

The algorithm used in the analysis, based on the betweenness value, produced 89 clusters. In addition to a number of small clusters, some really large ones have emerged. The largest cluster has 122 elements, and is organised around CERTH (Greece), which also plays a leading role in the overall sample (*Table 3*).

Table 3. Ten most important participants by betweenness in the biggest cluster

Name (abbr.)	Country	Betweenness
CERTH	Greece	138422.56
DTU	Denmark	28936.06
RISE	Sweden	15094.09
ROBOTNIK	Spain	10627.14
NCSR „D"	Greece	10251.51
CERCA - i2CAT	Spain	7728.25
KEMEA	Greece	7118.78
VICOM	Spain	6970.09
ADS	France	5900.21
VIPO AS	Norway	5727.00

Source: own calculation

In addition, one other participant (DTU from Denmark) in the cluster has an outstanding betweenness value. 28 participants have a measurable betweenness value, but 92 have a value of zero. This may suggest that, with the right professional or scientific content, a hitherto less important research partner can build up links with even the most important member of the research network.

Summary

Unlike previous calculations in previous segments, the drone research project network, which can be broken down into a large number of clusters, shows a fairly high degree of interconnectedness and a high level of concentrated scientific collaboration. A robust analysis of this topic requires further research, which the current work can provide.

The obtained transitivity values are quite high, especially compared to the other indicators, based on the results of typical project networks (Fernandez de Arroyabe, Schumann, Sena, & Lucas, 2021), suggesting that the project linkage was probably based on a kind of acquaintance, on the basis of previous research contacts (Kürtösi, 2011).

The clusters are quite hierarchical, i.e. with a few central project participants and a few more participants of average importance, most participants in each cluster are not particularly important in terms of betweenness. This highlights the fact that with the right professional work there may be a chance to join clusters as they are not elite clubs. Thus, networking relationships that are peripheral from a networking point of view but scientifically fruitful can be built up without further ado, given a serious scientific-technical performance and a good project partnering strategy.

This is particularly important for institutions, companies and research institutes in countries like Hungary. Hungary has not played an important role in drone research so far, but it seems to be a growing priority in Hungary as well. Hungary is represented by 11 project participants out of 2245 project participants. Apart from SZTAKI, the University of Miskolc and the Centre for Astronomy and Earth Sciences, only companies from Budapest are involved. They did not play a central role in the projects, but they will certainly have a chance to move forward in the next funding period and, as mentioned above, new entrants will be able to enter.

The next funding framework programme (Horizon Europe) is likely to provide an opportunity for comparative analysis in the near future. (How has the structure of the thematic research network changed? What are the characteristics of the new clusters?) The project descriptions will be comparable between the two Framework Programmes (Horizon 2020 - Horizon Europe) using text mining tools and would reveal technical changes. Unfortunately, such a comparative approach was not possible in the FP7 - Horizon 2020 relation due to the relative subordination of drone research in FP7, but this seems to be an exciting research task for the future.

The growing possibilities for comparability also highlight the limitations of the current analysis. It is very difficult to compare these data with other ones. Of course, this can be done with project networks around other themes, but it would be pointless. Future comparative analyses could of course extend the statistical methodology used.

Acknowledgements

The research was made in frame of the project TKP2021-NVA-13 which has been implemented with the support provided by the Ministry of Culture and Innovation of Hungary from the National Research, Development and Innovation Fund, financed under the TKP2021-NVA funding scheme.

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