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Social Network Analysis in Wood Industry Projects

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Abstract – The study analysed H2020 projects in the wood industry using SNA methods. It was mainly performed using R. Based on the data set from CORDIS, an adjacency matrix was constructed and used to plot the network of project participants. Various network indicators were then calculated. In search of notable distributions in network research, several statistical methods (maximum likelihood, Kolmogorov-Smirnov test, moments, bootstrapping) were used to perform a goodness-of-fit analysis on the frequencies of the degrees to verify randomness or scale-freedom. The small-world nature was also investigated. The results show that the distribution of the degrees of project participants reflects multiple effects, whereas the number of project participations per project participant follows a power distribution; thus, the scale-freedom that has been emphasised in many scientific analyses is observed. The network indicators show that the network is not small-world, with a high number of Finnish participants among the central actors.

wood industry / project / SNA / Horizon 2020

Kivonat – Faipari projektek kapcsolatháló-elemzése. A tanulmány keretében a Horizont 2020 faipari projektjeit elemeztük hálózatelemzési (SNA) módszerekkel. Az elemzés során elsősorban az R statisztikai programozási nyelv hálózatelemzési és illeszkedésvizsgálati csomagjait használtuk. A CORDIS-ból kiszűrt adatállományra építve szomszédsági mátrixot írtunk fel, amely alapján felrajzoltuk a faipari projektrésztvevők hálóját, majd különböző hálózati mutatókat számoltunk. A hálózatkutatásban nevezetes eloszlásokat keresve többféle statisztikai módszerrel (maximum likelihood módszer, Kolmogorov-Szmirnov teszt, momentumok módszere, bootstrapping módszer) illeszkedésvizsgálatot végeztünk a fokszámok gyakoriságaira, az esetleges véletlen vagy skálafüggetlen jelleg igazolására. Vizsgáltuk a hálózat kisvilágjellegét is. Eredményeink alapján a projektrésztvevőkből felépülő projektháló fokszámainak eloszlása többféle hatást tükröz, ellenben a projektrésztvevőnként projektrészvételek száma egyértelműen hatványeloszlást követ, tehát a számos tudományos elemzésben kitüntetettnek tekintett skálafüggetlenség érvényesül. A hálózati mutatók alapján a hálózat nem kisvilágjellegű, s a központi aktorok között feltűnően sok a finn résztvevő.

faipar / projekt / SNA / Horizont 2020

1 INTRODUCTION

The analysis presented in this paper is an example of SNA (Social Network Analysis). The main research objective is to draw up and analyse the networks of mainly European institutions, research institutes and companies participating in Horizon2020 projects in the wood sector using network research tools.

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The different network indicators will measure the "development" of the network, i.e. how "efficiently" the network connects participants and how much it facilitates information and knowledge exchange. This is certainly important information for businesses, research institutes and other actors in the wood industry and can point the way forward. The research focused to a large extent on the degree (number of contacts) of the network participants. The different distributions of degree numbers may indicate the nature of the networks, their design, and the logic of their operation. The study of the scale-freedom is particularly important because in many areas of social life, it is typical that few nodes have many degree numbers, or many nodes have few degree numbers. When raising R&D resources, wood enterprises, research institutes and other actors are right to want to connect with the central actors in the networks, especially in the case of scale-free networks.

After many antecedents, the study of social networks has been a major focus of academic attention since the second half of the 1990s. In Hungary, it is largely due to the works of Albert-László Barabási (Barabási 2003). Barabási's contribution to the discipline – particularly in the field of science management and the IT implementation of existing theories – is also considerable worldwide (Barabási 2018). However, network analysis had been an important field of science for decades before that, with its maturation starting in the second half of the 1950s. The network analysis methods applied in this paper build on the results of recent decades. Therefore, we used the results of the model describing random networks/graphs (Erdős – Rényi 1960), the configuration model for networks with a fixed degree number distribution but otherwise composed of completely random links (Bollobás 1980) (Molloy – Reed 1995) (Newman – 2010), the small world model (Watts – Strogatz 1998) and the scale-free network model (Barabási – Albert, 1999).
Network analysis has a fairly well-established methodology. Some of the methods are related to different theoretical schools of thought, but from a theoretical point of view, it can be considered more as a "pattern" with a specific logic.

2 MATERIALS AND METHODS

First, the CORDIS downloadable dataset was converted into a workable relational database. It is possible to retrieve data from all Horizon 2020 projects using the database.

The pre-screening of wood projects was done using search terms, and the filtered dataset was then subjected to content analysis to reduce the dataset further. The wood production process (value chain) is featured in 197 of the 30,084 Horizon 2020 projects. (Novotni 2022) Of the 1,093 project participants, 550 were private for-profit entities, 227 were research organisations, 159 were higher or secondary education establishments, 64 were public bodies, and 93 were other organisations. The participants represent 41 countries, mostly from the European Union. The top 5 countries involved in most projects are Spain (142), Germany (119), Italy (98), France (89), and Finland (87).

A wood project (project participants') network is treated as an undirected network, in which the direction of connection between nodes is ignored. Regardless of their various statuses, scientific collaborations are commonly thought of as undirected connections. For example, we did not consider whether the participant is also a project coordinator. The analysis was performed using the R programming language (Novotni – Tóth 2022c). The R code makes the analysis easy to reproduce.

First, the vectors to store all the pairs of connections were generated. From this, we created a matrix and then an undirected graph. The next step was to create *the adjacency matrix*. The adjacency matrix is of great importance in network research. From the adjacency matrix, we were able to draw the connection network. The number of connections in a network can be recorded in the formula:

$$PE = \frac{N(N-1)}{2}, \tag{1}$$

where N is the elements of a network. The *density* in an undirected network can be written as:

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

where E is the number of edges. If all possible connections exist and everyone is connected to everyone else, the density is 1. With a density value of 0, no one is connected to anyone. Therefore, the density value is a number between 0 and 1, with higher values indicating a higher network density (Molnár 2020). The assessment of density is only straightforward when comparing networks of similar size.

Transitivity is the average probability. 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*, which can be derived from the clustering coefficient (the transitivity of a given node) (Barabási 2017). The clustering coefficient of the i-th node with degree k_i is:

$$C_i = \frac{2L_i}{k_i(k_i-1)}, \tag{3}$$

where L_i is the number of connections between the neighbours with k_i degree of the i-th point. Its value is always between 0 and 1. Average clustering coefficient for the whole network is:

$$\langle C \rangle = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{4}$$

based on clustering coefficient. The number of nodes (N) and the number of degrees (k) can be used to calculate the *total number of connections* with the formula:

$$L = \frac{1}{2}\sum_{i=1}^{N} k_i \tag{5}$$

in an undirected network. A fundamental characteristic of a network is whether it can be classified as scale-free. A network is called scale-free if its degree distribution can be described by a power function (Barabási 2017). The essence of scale-free networks is expressed by the moments of the degree distribution. The n-th moment of the degree number distribution is:

$$\langle k^n \rangle = \int_{k_{min}}^{k_{max}} k^n p(k) dk = C\frac{k_{max}^{n-\gamma+1} - k_{min}^{n-\gamma+1}}{n-\gamma+1} \tag{6}$$

in scale-free networks. True scale-free and random networks (normal or Poisson distribution) are quite rare, and most existing networks have a variety of effects at play in their formation and evolution. Therefore, a crucial question in network research is whether we can use a distribution other than random (Poisson or normal) or power distribution to describe the frequencies of the degree numbers. In statistics, this question falls under the topic of goodness-of-fit analysis. However, we need to clarify two seemingly trivial points about degrees.

The first problem is whether to treat the number of degrees per node as a discrete variable or as a continuous variable. The number of degrees is obviously a discrete variable, but it could be much higher, or even more diverse than the current one in the case of a larger network or more intensive cooperation. Moreover, the variable moves on a proportional scale. In such cases, for example, common statistical software introduces the concept of a "discrete variable treated as a continuous variable" and suggests the use of continuous analysis methods for the discrete variable (Acock 2018) (IBM Corp. 2020). The creators of the *fitdistrplus* package for fitting distributions and the authors of its vignette treat discrete variables with many elements as continuous (Delignette-Muller – Dutang 2020). However, for fit analysis methods for more common distributions, the applicability of continuous methods to discrete variables is controversial (Clauset et al. 2009).

Whether to use population or sampling statistical methods in the analysis was a similar problem. The problems of delimiting some characteristics of woodworking projects as a population, the not necessarily complete project network, and the inherently imperfect nature of data collection justify the choice of methods that "handle" uncertainties and imperfections, e.g. bootstrapping methods in our case. The project network that we are investigating as a possible representation of all possible project networks or as a possible sample of wood projects raises much more serious sampling issues than if we consider the set of wood projects registered in Horizon 2020 as a population. For this reason, we tended to lean towards the latter throughout the analysis. Nevertheless, we also followed the advice in the literature and performed the necessary statistical tests.

The standard goodness-of-fit test question may, therefore, be modified in that case. It is unnecessary to estimate whether the population satisfies the given distribution in the sample, but (with methodological caveats and caution) to determine instead whether the population itself satisfies the given distribution.

This is not a cardinal problem if you are not looking for exact parameters but just want to confirm or reject your hypothesis about the fit (Clauset et al. 2009) (Delignette-Muller – Dutang, 2020) (Gillespie 2020). Of course, all such controversial methodological issues should be approached with great caution. We attempted to choose the methods that give reliable results for almost "any" data set and exclude methods that give large deviations.

Using a discrete variable method, we tested whether the data series follows a Poisson distribution. A χ^2 test or a maximum likelihood method can be used (and was used) to test for a Poisson distribution. The procedure chosen can be used for a sample and a group considered as a population. We also checked whether the degree numbers follow a power distribution. Because of the uncertainties in calculations, it is worth using bootstrapping methods with higher machine requirements. The bootstrapping method performs a number of back-sampling and estimation operations on the data set under consideration and then cumulates the resulting values.

The selected computer algorithm is generally used for sampling procedures. Since we treat the group as a population here, we have not modified the procedure for sampling and the algorithm handles this well. The difference between the two results would otherwise be minimal. A *Cullen-Frey diagram* (Kurtosis-Skewness diagram) showing the possible values for the most common distributions has also been produced (Cullen – Frey 1999). Since skewness and kurtosis are not robust (small parameter changes can show large variations), we chose a non-parametric (non-normal) bootstrapping procedure with $boot = 1000$ (Efron – Tibshirani 1994). This procedure gives reliable and visually well-plotted results. The graph was generated for both discrete variables and continuously treated discrete variables.

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 small diameters are called "small world" (Barabási 2006). The formula:

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

describes the diameter of a network. Equation (7) describes the small-world phenomenon (Barabási 2017). Since equation (7) gives a better approximation for the average distance ($\langle d \rangle$) between two randomly chosen nodes than for d_{max} in most networks, the formula:

$$\langle \mathrm{d} \rangle \approx \frac{\ln \mathrm{N}}{\ln\langle \mathrm{k} \rangle} \tag{8}$$

describes the small-world phenomenon. Thus, for a small-world, "small" means that the average path length or diameter depends logarithmically on the length of the network.

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). The betweenness of v node is:

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

where σ_{st} is the number of shortest paths between nodes s and t, and $\sigma_{st}(v)$ is the number of paths that pass through v of these nodes. The normalized form is often used, where the expression (9) is divided by $(N-1)(N-2)/2$ for undirected graphs. The expression:

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

is also often used as a normalised form. In both cases, the value falls within the range [0.1]. The betweenness and the number of degrees can be used to filter the most important participants. Many other indicators can be calculated on the basis of the literature, but this article includes only the most relevant ones for the purposes of analysis.

3 THE RESULTS OF THE ANALYSIS

3.1 Drawing the connection network

The adjacency matrix results in a matrix of 760 rows and 760 columns. Therefore, the number of nodes is 760. The size of the adjacency matrix makes it impossible to publish here, so it has been made available permanently at a specific website (Novotni – Tóth 2022a).

Starting from the adjacency matrix, *Figure 1 shows* the network of connections between project participants.

The mapped network of connections alone reveals little about the nature of the network. It does show that the majority of project participants are connected, but peripheral groups and participants also exist.

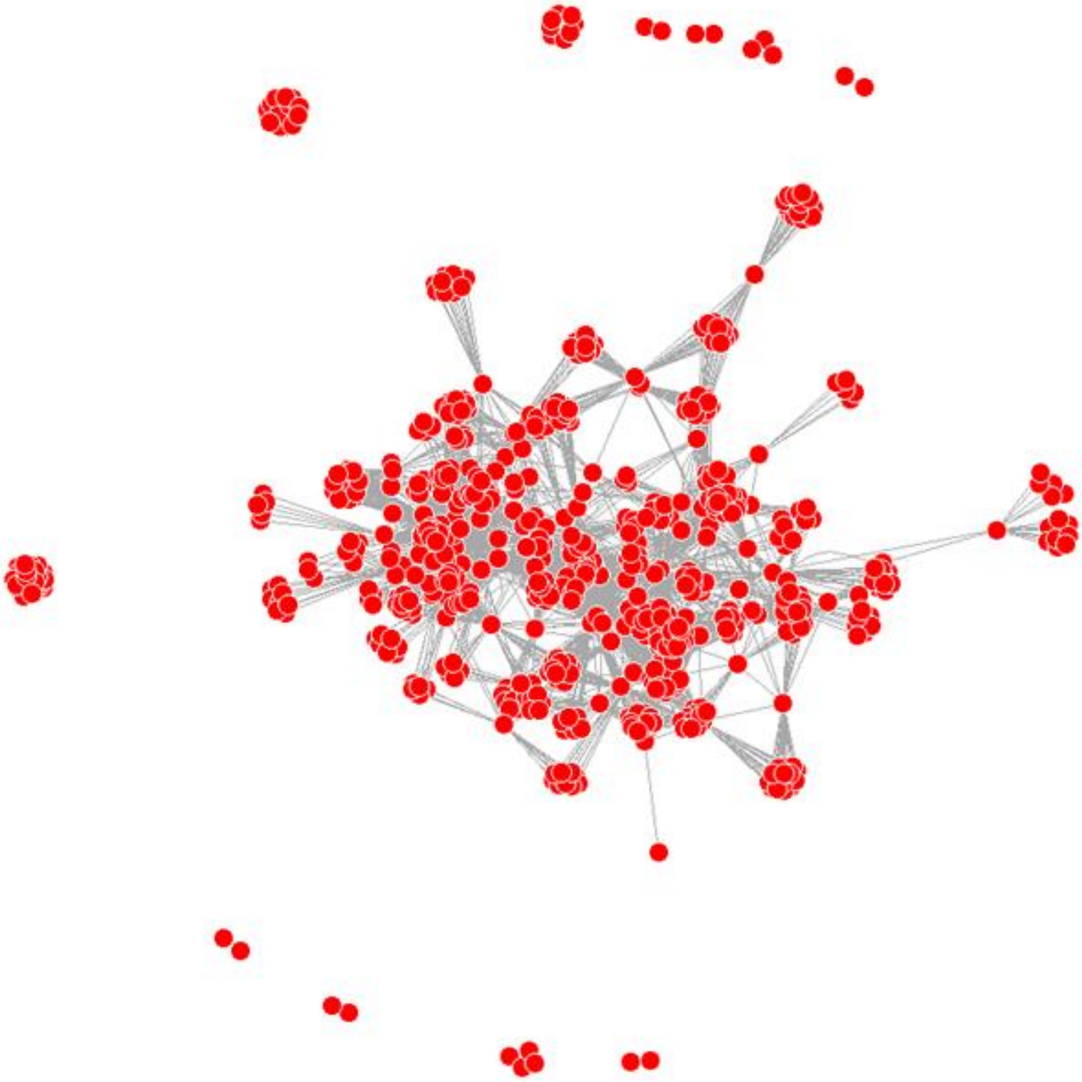

Figure 1. Network of project participants

3.2 Calculated values of network indicators and results of the fit test

The density value based on equation (1),(2) is 0.028. A reliable evaluation of the result would require the values of networks similar in size and type. The value does not seem high. There are two possible reasons for this. Perhaps the links between wood industry institutions, research institutes and companies are poorly developed. However, it is more likely that the studied networks describe the R&D intensive elite of the wood industry. Due to the finite nature of the resources, the number of project participants obviously lags significantly behind the number of potential participants.

The value of the transitivity calculated from equation (3),(4) is 0.65, which is also subject to the uncertainty as indicated in the previous indicator. However, this value seems to be high despite the uncertainty, suggesting that the "my friend's friend is my friend" phenomenon is quite pronounced in the wood industry project network. This suggests that the participants in wood industry projects are basically the "top" of the wood industry and are typically connected through established contacts, which is unfortunate for the outsiders.

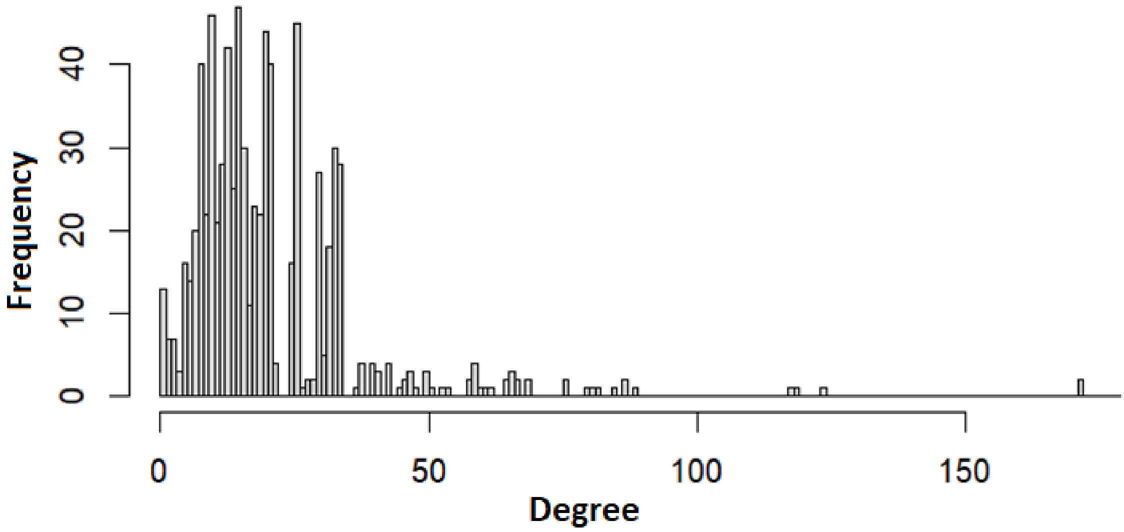

Figure 2. Frequencies of degrees

Figure 2 depicts the degrees calculated from equation (5). The result of the maximum likelihood estimation is: $G^2 = 5992.119$, $df = 63$, $p = 0$, $\lambda = 20.88421$. In the case of $\alpha = 0.05$ $c_{crit} = 82.53$ $G^2 > c_{crit}$ and $p < \alpha$; therefore, H_0 is rejected. The degree numbers are not Poisson distributed. The *rootogram*, which shows how much our empirical values should be shifted to obtain the desired distribution, confirms our results (*Figure 3*).

A Poisson distribution of degree numbers would have indicated that the majority of participants had an average degree. It is assumed that the participants in these networks are all the same, with no one in a distinguished role. By examining the formation of a network of such points, we find nodes of equal rank. The results suggest that this can be ruled out completely, as there are clearly nodes with privileged roles in the wood industry project network. This confirms our previous results.

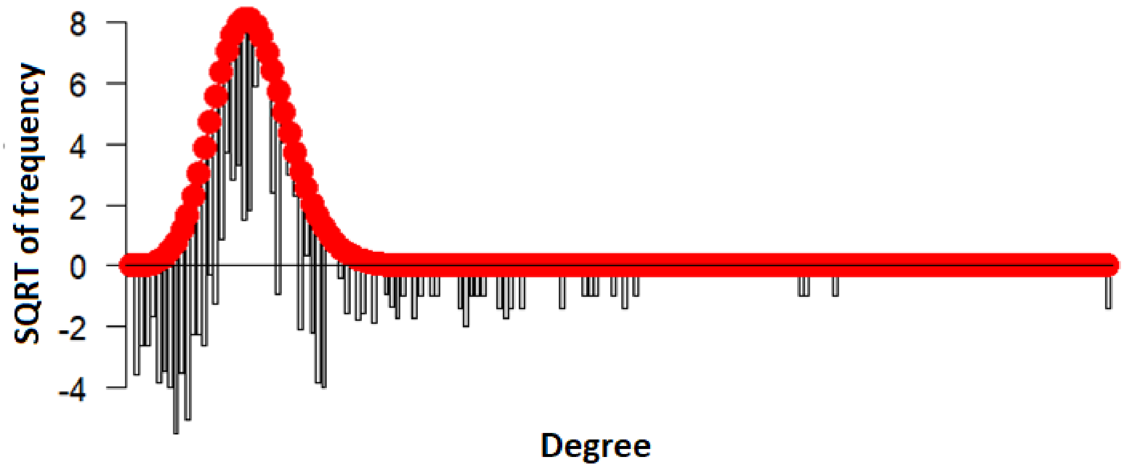

Figure 3. Rootogram of degrees

The goodness-of-fit (power distribution) test resulted in the following values: $\alpha = 4.45$, $x_{min} = 58$, $p = 0.99$. Given the high p-value obtained, we should accept H_0, but this would be a wrong conclusion since for $x \geq 58$ we can clearly say that our empirical values follow a power distribution. Therefore, H_0 is not accepted.

The values obtained with the 5000-iteration bootstrapping method are: $\alpha = 4.35$, $x_{min} = 51$, $p = 0.67$. Accordingly, the data series can be classified as power-distributed with lower confidence and a somewhat lower value, but the result does not change the fact that H_0 is rejected.

Using the Cullen-Frey diagram, we can also test the possible distribution of the degree numbers. The Cullen-Frey plot of the discrete variable confirms our previous results; the variable is not Poisson distributed. It also does not fit into the range of the negative binomial distribution (*Figure 4*).

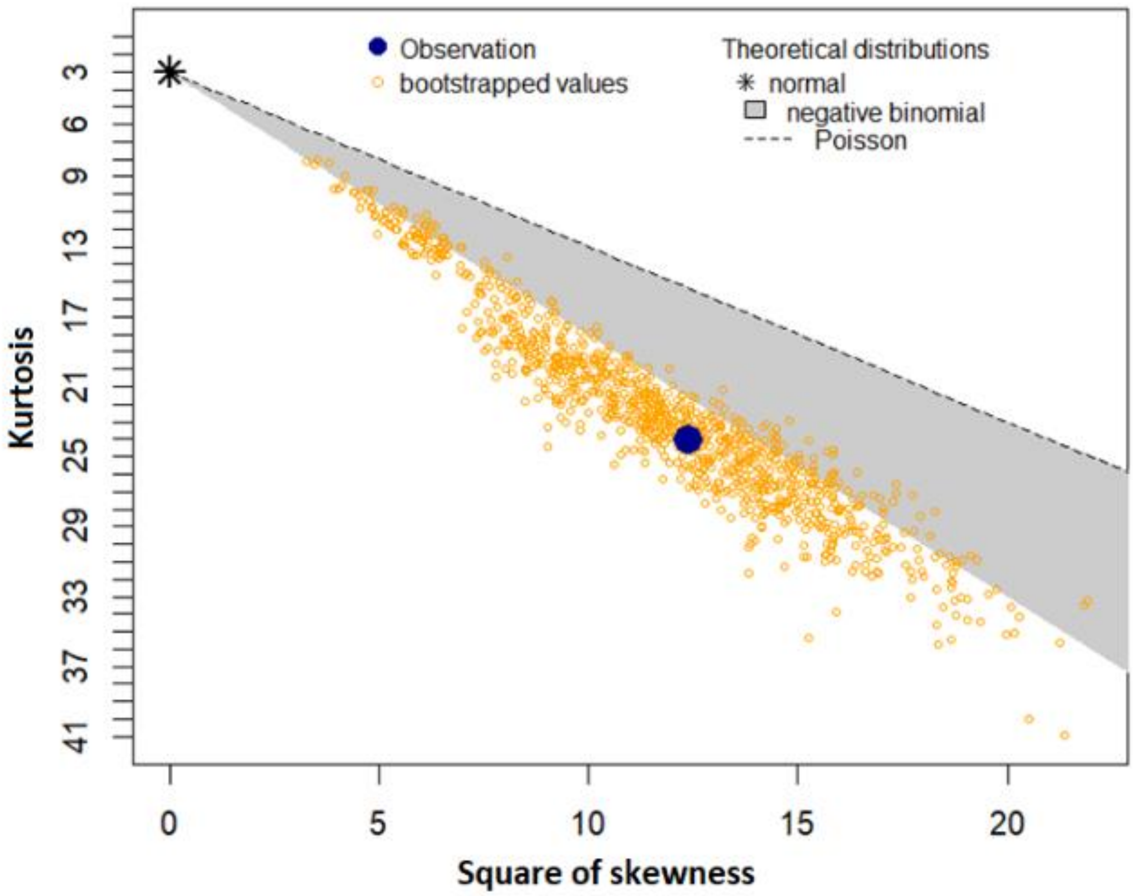

Figure 4. Cullen and Frey graph (discrete variable)

The Cullen-Frey diagram (*Figure 5*) for the discrete variable treated as a continuous variable shows that the distribution of the degree numbers lies between the gamma and lognormal distributions and outside the range of the beta distribution. A value of kurtosis much larger than 3 indicates a high peak. In such a case, the fit of the Weibull distribution is also limited (as for the other three "skewed" distributions). Distributions other than the Poisson and power distributions may suggest specific regularities that are rare in economic and social processes, but this does not appear to be the case here.

Based on the results obtained, we can assume (and this is the most likely assumption) that the "skewed to the left" distribution was influenced or shaped by a combination of random factors and factors that act towards scale-freedom. The result obtained can also be deduced from the nature of the search for partners in the projects. As the network grew, network participants tended to prefer to connect to nodes that were already recognised or had many network connections at the submission stage (preferential connection), but this also brought them into contact with other project participants, so that the frequency of the lowest degree numbers was inevitably lower than in scale-free networks. Moreover, the funding scheme favours projects with multiple actors.

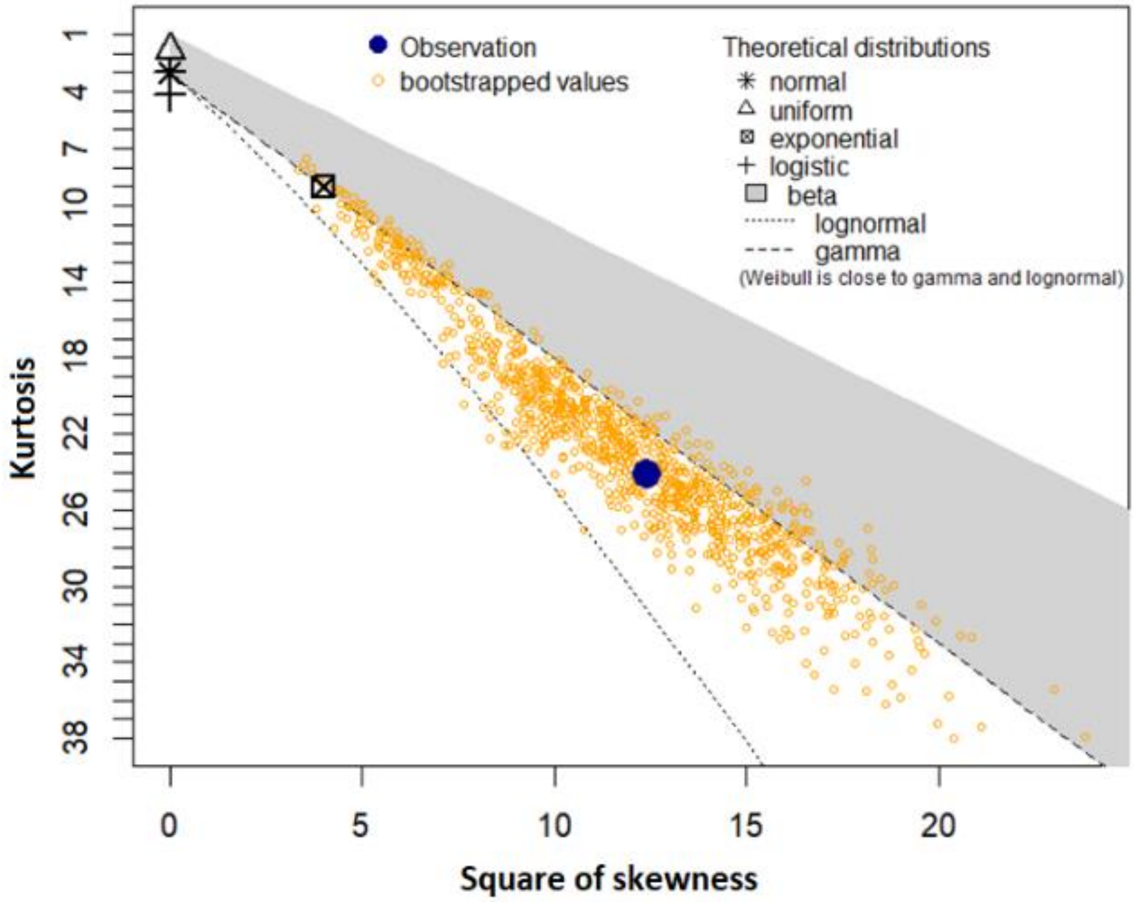

Figure 5. Cullen and Frey graph (continuous variable)

Figure 6, which shows the frequency of participation in projects per participant, seems to support this relationship. The goodness-of-fit (power distribution) test performed on these values (Novotni – Tóth 2022b) yielded the following values: $\alpha = 3.18$ ($\sim\gamma$), $x_{min} = 1$, $p = 1$.

While the distribution of degree numbers did not follow a power function distribution, the frequency of project participation showed an almost perfect fit from the initial value. In other words, scale-freedom, nowadays considered an important phenomenon in scientific analyses, applies to the frequency of project participation. (Although α is slightly higher than 3.)

The network diameter is 6. The standard deviation of the network diameter is $\sigma = 0.94$. Therefore, the relation in equation (8) is not satisfied: $6 \not\approx 2.18$ ($6 \pm 0.94 \not\approx 2.18$). The average diameter is only 3.1, but equation (9) is still not clearly satisfied: $3.1 \not\approx 2.18$ ($3.1 \pm 0.94 \not\approx 2.18$). The diameter is high compared to the size of the network, which suggests there are still peripheral players compared to the core in this project network, even though we can assume that we are dealing mainly with the scientific and technological elite of the wood industry and the wood industry project network obviously covers only a small part of the wood industry.

Based on the above values, the network of wood projects can be considered as small-world or not at all or only to a very limited extent. More network connections would be needed to be considered small-world. However, this does not necessarily mean that the network of contacts outside the projects cannot be considered small-scale. Rather, it is more likely that due to the average number of participants per project, barriers to entry and the attraction to those with intensive networks, small and/or non-knowledge intensive wood actors are simply under-represented in the sample and not all contacts are recorded as project contacts. The network is inherently fragmented from the point of view of the wood industry. It also hides the elites. The question is who, from a network research point of view, plays the decisive role in this network, and how far this intersects with the results of studies from other aspects.

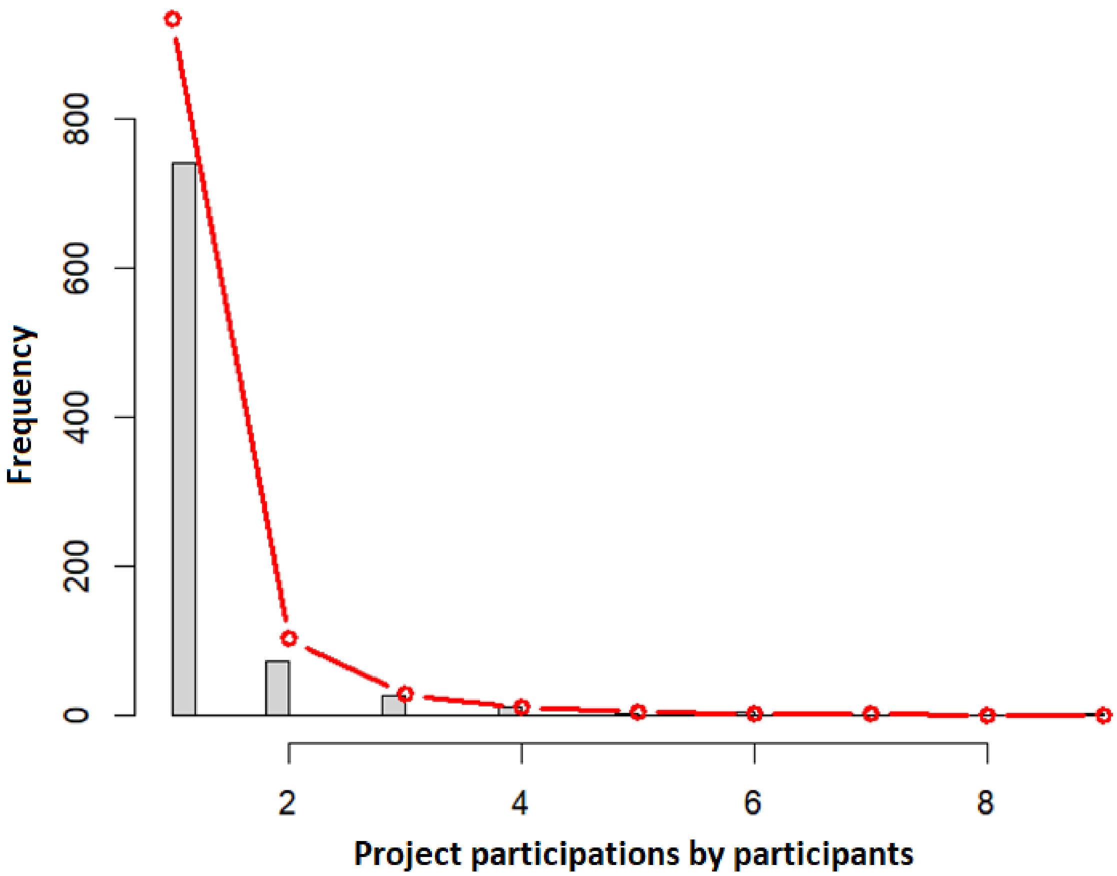

Figure 6. Frequency of participations

Table 1 lists the five project participants ranked as the most important by the degree numbers; *Table 2* by the betweenness ranking.

Table 1. Central participants by degree

Name	Country	Degree
Luonnonvarakeskus	Finland	172
Teknologian tutkimuskeskus VTT Oy	Finland	172
Fraunhofer-Gesellschaft	Germany	124
Rina Consulting S.p.A.	Italy	119
Tecnalia Research & Innovation	Spain	118

Table 2. Central participants by betweenness

Name	Country	Betweenness
Teknologian tutkimuskeskus VTT Oy	Finland	45804.83
Luonnonvarakeskus	Finland	40508.59
Fraunhofer-Gesellschaft	Germany	34836.24
Metgen Oy	Finland	18980.53
Tecnalia Research & Innovation	Spain	15980.73

There is a large overlap between the two tables. Many Finnish participants are among the central actors. Considering the weight of Finland's wood industry, the prominent role of Finnish participants is not surprising. However, based on our previous studies, most of the coordinator roles in woodworking projects were filled by participants from Spain, although Finnish participants held second place ahead of the French, Italian and British participants. However, in terms of the total number of participations in wood projects, the Finnish participants were only fifth (Novotni – Tóth 2021).

Therefore, the Finnish participants were the most important network participants, despite their relatively "low" number of participations in wood industry projects. This may indicate conscious networking, strong project participation and a long-term, knowledge-intensive strategy that goes beyond direct resource mobilisation. It is perhaps also worth noting that the two prominent Finnish institutions in the network are both research organisations and have a strong integrative role in the Finnish wood industry, which offers a potential lesson in the strategy-making process for less well-endowed but similarly small countries.

4 CONCLUSIONS

The network between participants in wood industry projects is neither random nor scale-free. On the other hand, the distribution of project participation per project participant clearly shows a power distribution, i.e. the distribution is scale-free. Meanwhile, the project network is not a small-world, i.e. there is not a sufficiently strong project network of connections in the wood sector. In any case, the central role of the Finnish participants is interesting as our analysis using other methods and other criteria did not show such dominance.

Based on the direct results, it is reasonable to assume that the real network beyond the wood industry projects may have properties approaching scale-freedom, which suggests that there is almost certainly a knowledge-intensive, vibrant network of connections at the centre of woodworking research, one that is much more central than the project network would suggest. Unfortunately, in addition to the centre, there are also a large number of peripheral players. There are many more of these than appear in the wood industry project network. Also, the nature of the projects makes some participants less peripheral. In particular, those involved in a small number of projects but otherwise with many participants.

Participating in these networks is an important objective for everyone in the industry. However, we have seen that these networks presumably describe the elite of the wood industry. Barriers to entry into these networks will continue to be a given, and the competitive advantage of entities with international project experience will continue to increase, both in terms of the chances of winning R&D funding and at the technological level. The central role of Finnish participants indicates that participants from small countries can also play a central role in wood research projects through smart strategies; however, this requires the right wood industry potential.

In the absence of such endowments, a smart strategy for those outside the elite club would be to cooperate with participants in international wood projects, not to obtain EU funding primarily but to mutually exploit scientific, technological, and business benefits. Of course, potential actors with emerging knowledge-intensive activities may target joining wood sector projects during the next funding period, but they will certainly face a difficult challenge. For those with project experience, the key question is to what extent they can build on the research and technological development carried out with EU funds to collaborate with others (especially with production companies) for mutual benefit. Finnish participants are themselves quite integrated organisations at the national level, i.e. for Hungarian project participants, R&D integration at the national level could be a first step towards strengthening international cooperation.

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