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Too many options: How to identify coalitions in a policy network?

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ABSTRACT

For different currents in policy analysis as policy networks and the Advocacy Coalition Framework (ACF), identifying coalitions from policy beliefs and coordination between actors is crucial to a precise understanding of a policy process. Focusing particularly the relational dimension of ACF approaches linked with policy network analysis, determining policy subsystems from the actor collaborations and exchanges has recently begun offering fertile links with the network analysis. Studies in this way frequently apply Block Modeling and Community Detection (BMCD) strategies to define homogeneous political groups. However, the BMCD literature is growing quickly, using a wide variety of algorithms and interesting selection methods that are much more diverse than those used in the policy network analysis and particularly the ACF when this current focused on the collaboration networks before or after regarding the belief distance between actors. Identifying the best methodological option in a specific context can therefore be difficult and few ACF studies give an explicit justification. On the other hand, few BMCD publications offer a systematic comparison of real social networks and they are never applied to policy network datasets. This paper offers a new, relevant 5-Step selection method to reconcile advances in both the policy networks/ACF and BMCD. Using an application based on original African policy network data collected in Madagascar and Niger, we provide a useful set of practical recommendations for future ACF studies using policy network analysis: (i) the density and size of the policy network affect the identification process, (ii) the “best algorithm” can be rigorously determined by maximizing a novel indicator based on convergence and homogeneity between algorithm results, (iii) researchers need to be careful with missing data: they affect the results and imputation does not solve the problem.

1. Introduction

Over the past two decades, there has been increasing interest in network analysis, particularly in multiple social science disciplines. One of the most important problems is related to the identification of different social communities in a specific network (Borgatti et al., 2009). This issue is crucial in the field of policy process theory in political sciences, which is an analytical approach used to understand and study how public policies are formulated, adopted and implemented because different political actors never act alone. In a specific policy process, they are unable to impose their will without any coordination. In this sense, observing how actors collaborate, interact and coordinate themselves in terms of policy subsystems is crucial to understanding which actors are doing what and how (Satoh et al., 2021). From the seminal work of Sabatier and Pelkey (1987), Sabatier (1987) and Sabatier and Jenkins-Smith (1993), the Advocacy Coalition Framework

(ACF) is one of the most important approaches supporting multiple theoretical foci. An advocacy coalition acts within a policy process and, therefore, represents more than just the dynamics of interactions and positions within the network structure. The ACF assumes that coalitions formed within policy subsystems are united by shared policy beliefs (Jenkins-Smith and Sabatier, 1994; Jenkins-Smith et al., 2018). The literature distinguishes three hierarchical levels of actor policy beliefs from which they seek potential allies or identify their opponents. *Deep core* beliefs are fundamental normative beliefs that are unlikely to change (such as political or religious ideologies); *policy core* beliefs are normative and empirical beliefs that guide actors' strategic behavior in trying to realize the deep core beliefs in a given policy subsystem (also unlikely to change); *secondary beliefs* are preferences for specific policy tools or targeted policy proposals to implement the policy core (Ingold, 2011). In a policy subsystem, there are typically two to four advocacy

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coalitions, one of which dominates the political influence scene (Weible et al., 2009). ACF provides a framework for identifying aggregates of actors in a coalition when they are engaged in relatively high levels of coordination and share similar beliefs with a particular emphasis on policy core (Sabatier and Weible, 2007). Traditionally, ACF studies focus on political coalitions driving policy processes and policy change, with a large number of empirical applications throughout the world: in North America (Weible, 2007; Ansell et al., 2009; Howe et al., 2021; Sabatier and Jenkins-Smith, 1993; Weible et al., 2016), in Western Europe (Gronow and Ylä-Anttila, 2019; Ingold et al., 2017; Nohrstedt, 2010; Fischer, 2014; Weible et al., 2016) and more recently in Asia and Africa (Osei-Kojo et al., 2022; Henry et al., 2014; Li and Weible, 2021; Sengchaleun et al., 2022).

Since the 2000s, different ACF studies have formalized the study of actors' formal and informal coordination processes to understand the governance in different steps of the policy process. In this way, structural criteria such as control and circulation of resources following hypotheses of resource dependence theory become a fundamental complement of the classical policy beliefs to capture actor subsystems (Weible, 2005; Weible and Sabatier, 2005; Ingold, 2011; Matti and Sandström, 2013). Complementary with classical perspectives focused on beliefs, this current in ACF uses social network analysis (SNA) and mobilizes data from coordination relationships (collaborative, agreements, disagreements and resources exchange) to approximate intra-coalition cohesion. In this way, the ACF literature recognizes the crucial contribution of network analysis as an indispensable tool for the study of policy processes (Smith, 2000; Weible, 2005). As a result, advocacy coalitions take shape around public policy issues and/or programs and, using the relational power structure and degrees of coordination between actors, seek to condition their outcomes (Sabatier and Weible, 2007). A policy subsystem thus constitutes a modelable network in which the organizations are the vertices (or nodes), and the various exchange relations form the links (or edges). Approaching political processes in terms of networks makes it possible to provide analytical content to the fundamental notions of cohesion, integration and conflict, providing important insights into group functioning which otherwise often remain intuitive (Ingold, 2011). Using SNA makes it possible to study both the relational and structural properties of a policy subsystem to identify clusters and key players (Varone et al., 2017). Empirically, a large proportion of recent studies have tried to integrate policy network analysis¹ into the ACF by examining coalitions based on the existence of coordination relationships and analyzing whether beliefs are also aligned (Ansell et al., 2009; Gronow and Ylä-Anttila, 2019; Ingold et al., 2017; Tindall et al., 2020; Kammerer and Ingold, 2021b). The work of Weible (2005), Weible and Sabatier (2005), Ingold (2011) and Matti and Sandström (2013) suggests that collaborative relationships between actors in a governance network are, at least in part, determined by ideological similarities. Some studies have added more subtlety to the approximation of intra-coalition relationships by incorporating criteria such as trust, influence (Henry, 2011; Henry et al., 2011; Calanni et al., 2015), and access to resources (Howe et al., 2023). These works postulate that the likelihood of actors collaborating increases when their beliefs are aligned, particularly when they share policy core beliefs relevant to the policy subsystem. In contrast, ideological disagreements will negatively affect these same relationships. Furthermore, both material and social capital may be determining factors, or at least complementary to shared beliefs, in the choice of actors to collaborate within a coalition (Henry et al., 2011; Howe et al., 2023). Finally, cross-referencing the ACF literature with social network analysis has led to the development of methods for identifying advocacy coalitions based on two complementary criteria:

¹ Policy network theory starts from the observation that the political scene is open to a variety of governmental, private, media, specialist and other actors sharing multiple links involving cooperation, information, resources, values and interests (Knoke, 1990, 2011; Rhodes, 2008).

1. Traditionally, an advocacy coalition is a cohesive political space based on belief homophily. Members of an advocacy coalition in the network must share "a set of normative beliefs and perceptions of the world, and act in concert to translate their beliefs into public policy" (Sabatier, 2014, p. 49). Coalitions convey norms between similar members because they share external beliefs or because a subgroup with a common representation of public policy is developed by the frequency of interactions during the policy process (Howe et al., 2021; Ingold et al., 2017; Ohno, 2022). This cognitive aspect is the central and most important condition in the ACF perspective.
2. Complementary to the first criterion, in order to transform their beliefs in public policies, the members of advocacy coalitions could collaborate, depending on the degree of belief agreement and the institutional setting the coalitions and policy processes are embedded in.² In this sense, members of the same coalition should have a higher flow of resources (such as information, funding, legal authority, collaboration) among themselves than with external actors, as well as relationships marked by collaboration, sharing of information and agreements. Conversely, advocacy coalitions should have weaker intra-cluster conflict relations³ than with actors belonging to other clusters. A coalition then includes actors who are structurally equivalent and/or have dense mutual interactions (Adam and Kriesi, 2007; Varone et al., 2017). Actors are structurally equivalent if they have a similar pattern of relationships in the network, i.e., they have similar patterns of ties with other actors, regardless of their direct ties to each other, especially regarding the network of collaborations and disagreements (Sabatier and Weible, 2007; Howlett et al., 2018). This involves grouping actors who belong to the same "social category", i.e. who supposedly play a similar role in the network and may show homogeneous beliefs due to shared cultural norms and resources (Marsden and Friedkin, 1993). Concerning the criterion of density of mutual interactions, the homophily hypothesis in ACF assumes that actors who seek to influence the outcomes of a public policy on the basis of shared beliefs develop collaborative links and tend to share more resources (Henry, 2011; Henry et al., 2011; Calanni et al., 2015). In other words, actors in the same coalition are in the same structural position and/or have dense mutual interactions and coordination is made possible by shared goals, beliefs, values, and interests. In the end, this second criterion is necessary but not sufficient without the first one to characterize a policy coalition from the ACF perspective.

Thus, the second criterion, articulated with the first one, implies partitioning a network into cliques of nodes (also called sub-networks,

² We point out to the reader that the degree of both intra- and inter-coalition collaboration is dependent on the degree of belief agreement, as well as the institutional setting in which the coalitions and policy processes are embedded. If we venture away from an ACF focus to consider other theoretical currents in the policy process theory, such as the literature on social capital, civic capacity or collaborative governance, it is notable that, given the diversity of contexts, a similar compromise may emerge with regard to beliefs. Some scholars will highlight the diversification of coalition strategies, ranging from coalition formation based on highly cohesive beliefs (strong homophily) to more inclusive coalition formation, integrating a greater diversity of viewpoints for strategic reasons (access to resources, influence in decision-making, etc.). These works also highlight the particular roles of policy brokers in developing these strategic coalitions and in cross-coalition collaboration. (see, for example (Ansell et al., 2009; Calanni et al., 2015).

³ Different studies in ACF use the disagreement ties in the decision process to identify the conflicts between groups or coalitions (Henry, 2011; Henry and Ingold, 2011; Ingold et al., 2017). In these papers perceived agreement/disagreement links, are viewed as a proxy of belief oppositions and help authors to observe coalitions.

clusters, blocks or communities) that are structurally equivalent and/or whose division presents a strong modularity. These two conditions do not appear to be complementary, as identifying an advocacy coalition can result from grouping actors into homogeneous clusters and/or structurally equivalent blocks depending on the context and the research question (Varone et al., 2017). These nuances can be attributed to differences in the community detection algorithms used by researchers. Variations in the definition of a community and the resulting methods of grouping actors differ from one algorithm to another, leading to relatively different cluster compositions. Let us take a closer look at how those algorithms differ, why, and how researchers can determine the clustering method and, thus, the algorithm that will allow them to capture the membership of coalitions that most closely resemble the reality of the political scene.

A wide variety of block modeling and community detection (BMCD) methods have been developed, borrowing strategies from various disciplines such as sociology, physics, biology and computer sciences and relying on nuanced definitions of a “community”. With regard to policy networks, for example, the advocacy coalition detection phase is already the subject of two different approaches to what constitutes a cluster. The first approach consists of detecting structurally equivalent communities and is based on algorithms belonging to the blockmodeling field. Blocks are simplified or reduced matrices of the network grouping structurally equivalent actors. This information is extracted from the adjacency matrix, and the blocks are generally made up of either zeros, corresponding to the absence of links, or ones, when a link exists. For valued data, the blocks are expected to contain similar values (Doreian et al., 2005). The second approach involves the community detection family of algorithms, which focuses on the internal cohesion we expect to find within coalitions. Community detection aims to identify distinct, relationally separated groups composed of nodes with a higher probability of being connected to each other than to members of other communities. Optimizing the modularity score – the difference between the proportion of links belonging to a given community and the proportion expected if the links were randomly distributed (Newman and Girvan, 2004) – is a regular component of this algorithm family.⁴ Within these families of algorithms, we subsequently find many different heuristic methods.⁵

Variations in how policy subsystems are measured can be perceived as a strength of the framework that affords it considerable empirical applicability (Weible et al. 2019). However, a diversity of methods undoubtedly provides relatively different results, and since they do not address the same criteria, they are difficult to compare (Kim and Moon, 2021; Metz et al., 2021; Weible and Sabatier, 2005; Herzog et al., 2022; Markarda et al., 2015; Ohno, 2022; Kammerer and Ingold, 2021b; Fisher et al., 2013). In the BMCD literature, it is accepted that an algorithm is efficient if it provides, in a reasonable time, a partitioning that closely matches the clusters of the network, whose community structure is known (Fortunato and Hric, 2016). Several studies have been conducted to compare the performance of algorithms (Yang and Algesheimer, 2016; Danon et al., 2005; Fabiano and Liang, 2014) and to develop selection methods (Smith et al., 2020; Bothorel et al., 2021). These studies propose accuracy measures based on the comparison of validation metrics, the similarity between the results of the algorithms and the reference partitioning, and the computation time (depending on the size of the network and the computing complexity of the algorithm). These performance metrics are then completed with a consideration of the study context. The results of these papers highlight the importance of taking into account the research question and the structure of the network, in particular its size and the strength

of its communities,⁶ and recognize that choosing an algorithm is neither an easy nor a neutral task. However, the literature dealing with BMCD is unfortunately disconnected from that relating to the ACF. Indeed, the BMCD literature has focused on evaluating algorithm performance over many networks, most of which are artificial, and since computation time is an evaluated criterion, structurally very large. However, in a real-world network case, it is common, even standard, that the known ground-truth communities and the expected number and composition of clusters are unknown. This is particularly the case in the ACF literature, which, in the absence of a reference partition and a systematic method, plebiscites the use of one algorithm or an algorithmic family without further justifying this choice and presenting explicitly why this approach should be better than the others (Kammerer and Ingold, 2021b).

Tackling these methodological questions that are crucial for the empirical ACF literature considering the relational coordination between actors through policy network analysis as important to characterize policy subsystems, we outline an original proposal introducing a three-fold contribution to the literature articulating ACF and network analysis from a methodological perspective. First, to try to solve the connection problem between the ACF and BMCD literature, the paper introduces a novel strategy based on recent developments in BMCD. Called the “5-Steps selection method”, this original approach makes it possible to select a reduced number of algorithms adapted to the density of the policy networks and to a specific research question. Future researchers using a network perspective will then be able to consider which of this selection of algorithms would be the most capable of revealing the real and robust communities from a set of contextualized policy network data. We, therefore, present a performance indicator to identify the best possible algorithm without any arbitrary choice. Second, this article applies the novel strategy to real-world policy network data from two policy processes in two different policy sectors in sub-Saharan Africa. The first network dataset was collected in 2018 and 2019 among the organizations participating in the Social Protection Working Group in Madagascar. Overseen by the Ministry of Population and UNICEF, this group of 36 national (ministries, public agencies...), international (multi or bilateral institutions...), private sector and civil society organizations (NGOs) was responsible for drafting national social protection policy. The second network dataset came from The Niger National Food Crisis Prevention and Management System (DNPFGCA). The DNPFGCA drives food crisis prevention and management policy through the Extended Consultation Committee (CEC). The original inter-organizational data was collected in 2022 from this committee structuring a collaborative network of national and international organizations regulated by the “Framework Agreement” signed in 2005 between the Niger government and international donors. Finally, the application results provide a valuable set of recommendations for further research on this topic: (i) the context matters, and the density and size of the policy network affect the identification of the set of possible algorithms; (ii) the “best method” can be rigorously determined by maximizing a novel indicator based on the convergence and the homogeneity between each pair of algorithms; (iii) researchers need to be very careful with missing data because they affect the results and imputation does not solve the problem.

The original method that we provide in this paper ambition to help future researchers choose an algorithm to identify clusters within specific and contextual policy networks, which can therefore serve the identification of coalitions. We specify that this method should be useful for the policy network analysis and ACF particularly; however, it should not be reduced to this methodological proposal, and

⁴ Highly modular networks have dense connections between nodes within clusters but sparse connections between nodes in different clusters.

⁵ For an overview of these, see Fortunato (2010).

⁶ Information about the strength of a community structure is captured by the mixing parameter μ which is the fraction of links that a node belonging to a community shares with nodes belonging to other communities (Lancichinetti et al., 2008).

different approaches are clearly needed depending on the context and the research question. More precisely, policy beliefs are crucial to characterizing the coalitions, and cluster identification can be a complementary step when researchers place more emphasis on coordination in the policy network.

This paper is organized as follows. Section 2 presents the novel and relevant 5-Steps selection method through the policy networks and BMCD literature relationships. Section 3 introduces the two inter-organizational policy network datasets collected in sub-Saharan Africa and used for the empirical application of the methodological proposal. Section 4 presents the application for the real-world policy networks, discusses the results and tests their robustness by introducing missing relational values. Finally, the last section discusses the methodological approach and summarizes the recommendations for future ACF research dealing with social network analysis tools.

2. Rearticulating policy networks and BMCD: A novel 5-step selection method

Establishing sub-networks, clusters, blocks, cliques, or communities is one of the most critical problems in network analysis, studied by the block modeling and community detection literature. Methods for identifying efficient algorithms are emerging, but there is no clear-cut answer to the determination of the most efficient method for real-world networks, particularly in the absence of ground-based partition. According to existing methods, selecting the most efficient algorithm can produce varying results, depending on the type of network studied and its structure. In the case of policy networks whose subsystems contain a reduced number of nodes, whose community structures can fluctuate widely, and whose communities can have two definitions leading to very different heuristic methods, the final choice of algorithm can be somewhat arbitrary. This fact is demonstrated, both implicitly and explicitly, in the field of community detection, e.g. Yang and Algesheimer (2016) whose summary table shows several algorithms suited to a given network; in Fortunato and Hric (2016, p. 39) who recognize that “Intuition and domain knowledge are indispensable elements to support or disregard solutions” given that in general “the final word on the reliability of a clustering algorithm is to be given by the user”; or in Chakraborty et al. (2017, p. 28) who conclude that “researchers are often in doubt while selecting an appropriate measurement metric” to use as optimization functions for detecting the community structure.

To select a community detection algorithm that is precisely suited to a given policy network and in the absence of ground-truth communities, we developed a useful and relevant 5-Steps selection method:

1. Test the algorithms frequently used in ACF studies
2. Select those whose results are consistent in the context
3. Compute the partitioning similarity between each selected algorithm
4. Select the algorithm that maximizes the relevant performance indicator
5. Perform a robustness test to check the number of clusters selected

2.1. Test the algorithms that are regularly found in the literature

Many studies adopting the Advocacy Coalition Framework use the Tabu Search algorithm available in the UCINET software package to find network communities based on the structural equivalence of actors (Kim and Moon, 2021; Metz et al., 2021; Weible and Sabatier, 2005; Herzog et al., 2022; Markarda et al., 2015; Ohno, 2022). The CONCOR algorithm also happens to fulfill this role (Kriesi and Jegen, 2001). Regarding community detection heuristics based on their structure, the software package igraph (Csardi and Nepusz, 2006) is widely used in network sciences, especially in the literature concerning comparing these methods. Kammerer and Ingold (2021b) select the Walktrap

method from among 12 algorithms as it showed the highest modularity score. We also observe the use of the hierarchical method in Fisher et al. (2013).

While both internal cohesion and structural equivalence are criteria allowing the definition of coalitions in a policy subsystem, in accordance with the ACF literature, the first step consists of selecting the algorithms based on those heuristics and adapted to the specific characteristics of the network to be studied.

2.2. Select those whose results are consistent in the context of the policy network structure

In the literature on the comparison of community detection algorithms, consistency is a criterion regularly applied to the results to ensure their reliability. The analysis of how accurate an algorithm is compared with the known partition is essentially based on how similar the supplied structure is to what is expected in terms of both the composition of the clusters and their number. In the absence of knowledge of the network’s community structure, it is then “determinant for the further exploration of the research question” to “identify such robust clustering, demonstrating an agreement between different methods” (Bothorel et al., 2021, p. 7). In real-world data applications, we advise refining the number of algorithms selected to answer the problem according to the convergence of the number of partitions. In particular, we consider it useless to include partitioning proposing a single cluster since this indicates that it is not adapted to the structure of the studied network. Other algorithms can provide a number of clusters that are relatively different from all the others. Each network has its specific characteristics; it is, therefore, the researcher’s job to determine which algorithms are unsuitable according to the proposed partitions.

2.3. Compute the partitioning similarity between each selected algorithm

Continuing the logic applied above, we use Normalized Mutual Information (NMI) to look for similarities in the cluster composition generated by the remaining algorithms. This indicator, measuring the similarity between two partitions, is widely found in the literature when measuring the accuracy of a method relative to the expected network partition (Fortunato and Hric, 2016; Danon et al., 2005; Yang and Algesheimer, 2016; Bothorel et al., 2021). NMI forms a confusion matrix N , whose rows correspond to the communities produced by one method (or the real communities where they are known) and whose columns refer to the communities produced by another. The element of N , N_{ij} , is the number of nodes common to the communities. A similarity measure between the partitions, I , based on information theory, is then computed such that :

$$I(P, \bar{P}) = \frac{-2 \sum_{i=1}^C \sum_{j=1}^{\bar{C}} N_{ij} \log(N_{ij} N / N_{i0} N_{0j})}{\sum_{i=1}^C N_{i0} \log(N_{i0} / N) + \sum_{j=1}^{\bar{C}} N_{0j} \log(N_{0j} / N)} \quad (1)$$

Where C is the number of communities given by the first method, \bar{C} is the number of communities given by the second; the sum on the i th row of N is denoted N_{i0} and the sum on the j th column is denoted N_{0j} . The score ranges from 0 to 1, 0 indicating that the partitions are entirely independent of one another, while 1 indicates that they are identical. An advantage of this approach is that it works even when the two methods being compared have a different number of clusters. However, this advantage has a flaw since the measure is sensitive to this difference and may favor a partition with more clusters (Zhang, 2015). Hence the importance of the previous step.

The NMI function can only compare partitions in pairs. To visualize the similarity between each partition, we compute a matrix whose elements at each intersection show the NMI between the algorithm shown on the x -axis and the y -axis. We thus obtain a visual representation of the convergence of the partitions, as well as the data relating to the latter, which will be used in the next step to construct our indicator.

2.4. Identify the best algorithm that maximizes the performance indicator

By exploiting the consistency-of-results criterion to the full, we believe that identifying the algorithm providing the best partitioning of a given network means choosing the one whose results maximize convergence with the others. To do this, we propose to maximize the average convergence of a given algorithm's partition while penalizing its heterogeneity by weighting the first term with the average difference in the value of the NMI of each algorithm with that of its "opponents".

$$I_{NMI}^a = \max(M_{NMI}^a \times H_{NMI}^a) \quad (2)$$

With a being a given algorithm.

The intuition behind this method is based on the fact that we seek the partition whose communities are consensual regardless of the method selected to form them and thus not ignoring a criterion defining a community in the sense of our research question. The first term of the equation calculates the average convergence with the other algorithms. We seek to maximize this information since it indicates how much the partitioning formed by one algorithm overlaps that of others.

$$M_{NMI}^a = \frac{1}{N} \sum_{a=1}^N NMI_a \quad (3)$$

Algorithms belonging to the same family should/will mechanically present a stronger average convergence pushed upwards by similar partitions since they are formed by methods applying the same logic. To prevent favoring an algorithm whose family is over-represented in the selection, it is essential to weight the first term by a heterogeneity indicator to account for the differences between a given partitioning and all the others. To do this, we take 1 as the maximum possible homogeneity, and we subtract the average of the difference in absolute value between the NMI of a given partitioning and the NMI of each of the others such that:

$$H_{NMI}^a = 1 - \left(\frac{1}{N} \sum_{a=1}^N |NMI_a - NMI_{a-1}| \right) \quad (4)$$

Finally, we maximize the resulting indicator I_{NMI}^a to select the partition most similar to all those we first considered.

2.5. Perform a robustness test to check the number of clusters selected

Among the selected algorithms, some will automatically determine the number of communities, while others leave it to the researcher to configure the latter. In this case, the lack of knowledge of the number of real communities appears problematic. We recommend initially relying on the number of clusters provided by the algorithms which automatically define this parameter. This recommendation is based on two intuitive elements: (i) the NMI function is sensitive to different numbers of clusters, and (ii) policy networks have a small number of actors that can be densely linked. In this case, it is unlikely that the classification of algorithms by our indicator will be disrupted by an underestimation or overestimation close to the real number of cliques, leading to a merger or split of communities.

To ensure that the number of communities retained is the best as possible, we propose to carry out a robustness test by comparing the partitioning proposed by the algorithm retained for several numbers of communities based on the common indicator associated with the algorithmic family (modularity, Dunn Index, R^2 , etc.). Suppose the number of communities that maximize the relevant indicator differs from the original partition. In that case, we recalculate the convergence indicator with the number of communities to ensure that the selected algorithm always maximizes the common indicator.

3. Original data from African policy processes

Before applying the described selection method, we present the data for the policy networks used. We consider two original cases of African policy processes in two different policy sectors. Niger and Madagascar are among the poorest countries in the world, each having aid-dependent regimes. Given the weakness of their institutional and financial resources, designing and implementing public policies in Niger and Madagascar depends on a political compromise between a wide variety of actors.

3.1. Madagascar's national social protection policy network

In Madagascar, social protection policy was undergoing concerted reformulation in 2018 and 2019. It was a "new public policy" based on a wide variety of existing programs (contributory and non-contributory) and whose negotiation process involved many actors. As mentioned in the previous section, following the adoption of a "Plan National de Protection Sociale" (PNPS - "National Social Protection Policy") in 2015, the country adopted a "Strategie Nationale de Protection Sociale" (SNPS - "National Social Protection Strategy") for the period 2019–2023 in November 2018. The existence of such documents cannot conceal the complexity of the political processes taking place in the background and the compromise that underpins them. This strategy document is the outcome of deliberations carried out within the Social Protection Working Group (GTPS), which brings together different national and international actors. Created in 2017 on the initiative of the Ministry of Population, Social Protection and Promotion of Women (MPPSPF) and co-led by UNICEF, this think tank met regularly between 2017 and 2019. We believed that analyzing the network of actors starting from this forum was a relevant analytical input in order to shed light on the interplay of actors, identify and specify possible coalitions that would influence future social protection policy, highlight potential points of ongoing and impending conflict, and identify brokers and powerful actors.

Our analytical approach focused on the policy network of actors involved in developing social protection policy in Madagascar. National politics is explored on the basis of this policy network built from the observation of the GTPS, which brings together a range of stakeholders, both international (international donors, international NGOs) and national (government actors - ministries and agencies, civil society actors and the private sector). In this sense, they carry with them the international and national balance of power. Drawing on the ACF research mentioned above, we focused on a particular type of relationship maintained between actors in the context of activities or exchanges relating to social protection over the five years preceding the survey: collaborative relationships, the strength of whose links ranged from 1 (weak) to 5 (strong).⁷

We took the GTPS as the starting point for our analysis. As the literature suggests, this type of working group is a particularly relevant subject for network analysis. To begin with, we adopted a nominalist approach based on a reputational strategy. Launched in 2017, this working group, co-piloted by the Ministry of Population, Social Protection and Women (MPPSPF) and UNICEF, convened several times between 2017 and 2019 in meetings open to the entire list or to thematic sub-groups. Using a sociometric questionnaire to collect information about the collaboration network in the GTPS, respondents were asked an open-ended question at the close of the interview to capture actor beliefs about the actors they considered to be important in the process of national deliberation on social protection and who

⁷ Covering different types of collaborative relationships such as joint participation in social protection project-programs, relationships involving financial support, technical partnerships, etc.

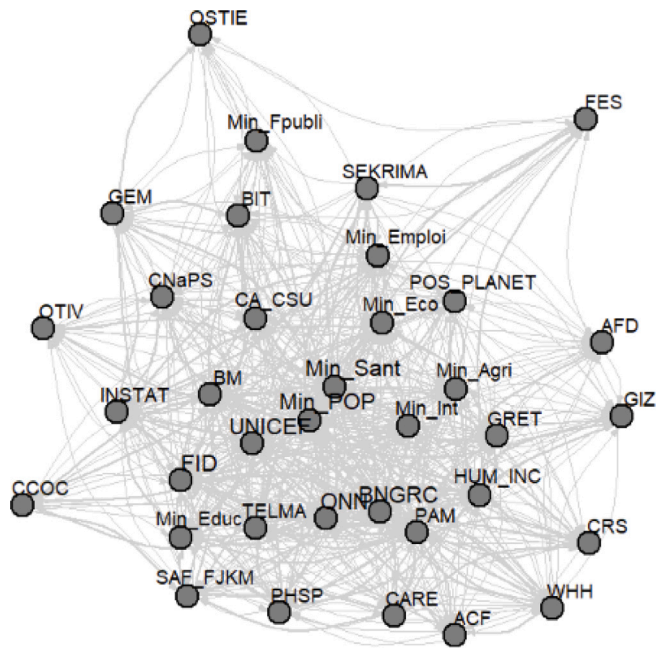


Fig. 1. Madagascar's social protection policy network (collaboration).

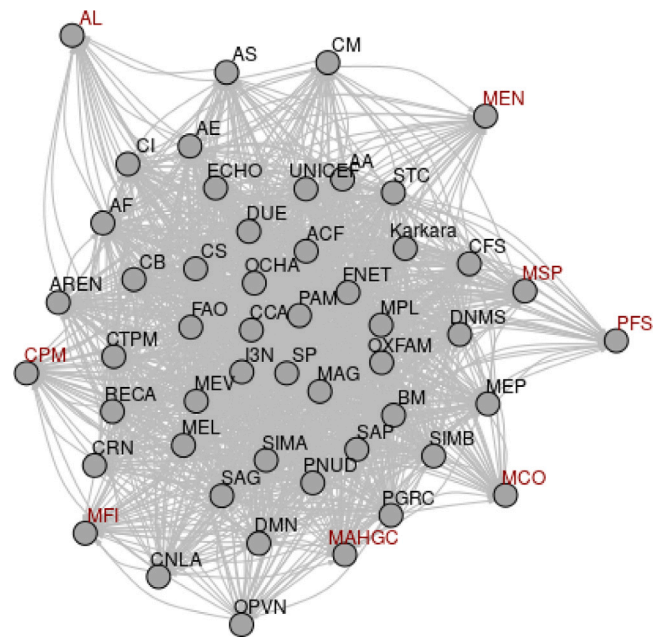


Fig. 2. Niger's national network against food crisis (sharing information).

were not listed (relational strategy).⁸ Any organization cited by five respondents was automatically added to our list. However, this open-ended question only resulted in the addition of one actor, the Prime Minister's office. The other three strategies (sign-in sheet, attendance at meetings, expert opinion) were mainly responsible for considerably thinning out the initial list, resulting in 36 actors from government or related structures, international donors, civil society and the private sector (Table A.2). The Fig. 1, which shows all the collaborative relationships between the 36 actors in our policy network, is dense,

⁸ The data are collected in two stages. The first stage consists of a socio-metric questionnaire to collect information about the collaboration network. Three other link types are collected: information sharing, agreement and disagreement. As the aim of this paper is to identify clusters based on relationships that best reflect the underlying structure of the networks, we will present our method based on the collaboration network in the case of Madagascar. This choice is in line with the work of Weible (2005), Weible and Sabatier (2005), Ingold (2011) and Matti and Sandström (2013) suggesting that these types of relationships are more likely to be initiated or reinforced by homophilous beliefs. The notion of collaboration can be interpreted informally as potential allies rather than relationships induced by formal institutions and decision rules. However, in a comprehensive ACF analysis, it would be advisable not to exclude the other links that can subsequently be mobilized to analyze the internal cohesion of the clusters identified via the alignment of beliefs and the degree of cohesion. In particular, agreement and disagreement networks are considered to be predictive factors for these two aspects (Henry, 2011; Henry et al., 2011). The second part of the survey consists of several modules for gathering information on the perceptions of the actors. These modules are made up of open and closed questions and Likert scales and help define the identity of the organization and the scope of its actions in the field of social protection, as well as its political convictions, ideals and preferences for specific instruments. In the ACF literature, the alignment of policy beliefs is a necessary condition for the existence of an advocacy coalition, which is then distinguished from a cluster structurally present in the network. However, this part of the questionnaire will not be used as this article focuses on identifying clusters in a governance network.

and organizations interact extensively with one another (Fig. A.3).⁹ Clearly, the form that emerges does not reflect a “center-periphery” or “brokered” but a “decentralized” policy network.

3.2. Niger's food crisis prevention and management policy network

The food crisis is one of the most critical issues in Niger, and the policy in this sector characterizes the core of the national development model. We considered the Extended Consultation Committee (CEC) which is led by the Permanent Secretary of the National Mechanism for Food Crisis Prevention and Management of Niger (DNPNGCA). The CEC was established in 2005 in response to one of the most severe food crises that affected the country. Under the prime minister, the permanent secretary of the DNPNGCA's role is to prevent, mitigate, manage and recover from the impacts of food crises, malnutrition and pastoralism on the Nigerien population. The DNPNGCA aims to offer a collaborative multi-actor system that is well-adapted to conducting the strategy and policies for food crisis prevention and management. Following the adoption in 2021 of the country's food security, nutrition and pastoral strategy for 2021–2025, the DNPNGCA implements the strategic program. This strategy document is the outcome of deliberations carried out within the CEC, which brings together different national and international actors such as international donors and NGOs, government bodies (ministries and agencies), civil society actors and the private sector (Table A.1).

We assume that the network of actors emerging from this working group, the CEC, is relevant in order to identify and specify possible coalitions that influence the country's food security, nutrition and pastoral farming policy, highlight potential points of disagreement and identify brokers and power actors. Indeed, this type of collaborative working group is a particularly relevant subject for political network analysis.

⁹ Fig. A.3 reports different network statistics: degree-in, degree-out, betweenness and closeness distributions.

Our analytical approach focused on the policy network of actors involved in developing food security, nutrition and pastoral policy in Niger. We used a classical sociometric questionnaire to understand the relationships between actors, such as the information network, and also to identify the strength of the links with 1 (weak) to 3 (strong). Unlike the Madagascar case, we decided to focus on resource exchange rather than collaboration because the DNP-GCA is, by definition, a collaborative working group to fight Niger's food crisis. Several aspects can explain this choice. First of all, the DNP-GCA is, by definition, a collaborative working group to fight Niger's food crisis; as such, the exchange of information appears to us to be more relevant in this case in order to capture privileged relationships between actors in the same coalition. Furthermore, the Advocacy Coalition Framework posits that actors in a network are fundamentally limited in processing information and consequently implement information selection heuristics based on their own beliefs. We thus assume that the exchange of information can be interpreted as a form of coordination, whether through beliefs or the integration of a logic of access to such essential capital. Finally, we confirmed this choice by cross-checking the information exchange and collaboration networks in Madagascar, which present a strong correlation, providing support for the hypothesis that these coordination and exchange networks can be highly interconnected.¹⁰ The 'information-sharing' link was collected over the three years preceding the survey. The interviews took place mainly between June and August 2022. In total, 42 of the 50 actors making up the CEC were interviewed. Non-respondents are indicated in red on Fig. 2. Indeed, applying the available-case analysis, i.e. an analysis on the network in which we keep the actors who did not respond as they are, as nodes with only incoming links, is a strategy that compromises the macro-structure analyses via block modeling as well as the micro-structure analyses of all members of the network, including non-respondents (Znidarsic et al., 2019).

Fig. 2, which shows all the information-sharing relationships between all the actors in the DNP-GCA policy network, is denser than Madagascar's and organizations interact extensively with one another (Fig. A.1).¹¹ Like Madagascar, the form that emerges also reflects a "decentralized" policy network.

4. Application of the 5-step selection method

In this section, we apply our algorithm selection method to the two datasets from Madagascar and Niger presented above. We then carry out robustness tests by treating missing values.

4.1. Findings

4.1.1. Testing the algorithms regularly found in the ACF literature

In accordance with the ACF literature, we select a set of 11 algorithms whose heuristics are based on internal cohesion and structural equivalence, the criteria we wish to use to define the coalitions in our policy subsystems. These algorithms are available either in UCINET or in the igraph package (version 1.3.1). Table 1 describes the functioning of the selected algorithms, as well as their specific characteristics and analytical implications.

¹⁰ The collaboration network contains 619 links, and its density is 0.49, and the information sharing network contains 564 links for a density of 0.45. The intersection of the collaboration graph and the information sharing graph, including the 515 links present in both between the same actors, indicates a density of 0.41. This represents about 83% overlap between collaboration and information-sharing relationships.

¹¹ Fig. A.1 reports different network statistics: degree-in, degree-out, betweenness and closeness distributions.

4.1.2. Select those whose results are consistent

We now refine the number of algorithms selected to solve our problem based on the convergence of the number of clusters. For the Niger study case, the selected algorithms provide a partitioning including 2 clusters in the absence of their manual parameterization, and based on those results, we keep this number of communities with algorithms whose parameterization must be done manually. For the Madagascar study case, the convergence occurs for 3 clusters. Moreover, the first analyses of the networks inform us that they are relatively well interconnected, particularly the Niger network with a high density of 0.68¹² and an average of 57 degrees per node (median = 55), confirming that the actors are highly connected (Fig. A.1). Although Madagascar presents a lower inter-connectivity (Fig. A.3), the network remains relatively dense (0.49) with 34 degrees per node on average (median = 34). We can, therefore, expect the mixing parameter μ of those networks to be high, leading some algorithms, such as Label Propagation, to underestimate the number of communities or not find any at all, and others, such as Spinglass and Edge Betweenness, to overestimate the number (Yang and Algesheimer, 2016). Given our results, we withdraw from our subsequent analyses those algorithms that return a single community including all our nodes, as well as those that provide a partitioning in which a single node is isolated from the network:

- Label propagation: a single community in both cases
- Minimum cut: isolates the node that is least connected to either network
- Edge betweenness: forms 43 clusters corresponding to all the nodes isolated in the Niger network, while it forms 11 clusters consisting mostly of isolated nodes in the Madagascar case.

4.1.3. Compute the partitioning similarity between each selected algorithm

We compute the NMI matrix of the remaining algorithms to visualize the similarity between the partitions and obtain the related data for the Madagascar and Niger policy networks.

We can now see that the algorithms converge differently depending on the network structure. The partitioning of the Niger network shows strong convergence between algorithms belonging to the same families but also between a few different heuristic methods, together with a fairly pronounced heterogeneity between algorithmic families (Fig. 3(a)). It should be noted that community detection algorithms based on structural equivalence as well as the hierarchical methods tend to gather the non-respondents in the same cluster. On the other hand, the partitioning of the Madagascar network appears to be more homogeneous overall (Fig. 3(b)). These figures underline the uniqueness of each case, making it essential to develop tools to select the best partition adapted to a given network.

4.1.4. Select the algorithm that maximizes the performance indicator

In the case of Niger, the Spectral algorithm maximizes the performance indicator (Table 2(a)).¹³ Spectral algorithm maximizes the average NMI, while the heterogeneity between the proposed partition and the clusters formed by the other algorithms is not strong enough to undermine this advantage. The result of the best clustering method identified by this novel approach can be visualized in Fig. 4(a). In this case, we have 2 cliques (sub-networks) in the graph representing the most convergent and the least heterogeneous policy groups.

¹² The network density, ranging from 0 to 1, measures the proportion of existing links in the network out of all possible links.

¹³ In our table, the leading algorithms (Spectral, Concor algo and Wlaxtrap for Niger's case and Wlaxtrap and Spinglass for Madagascar's case) all show the same result, although they are separated by a very marginal delta (more than two decimal places).

Table 1
Description of the selected algorithms.

Clustering (agglomerative) methods	
<p>The notion of distance in this family makes it possible to identify cliques through relational proximities (in the network) that favor the exchange of resources. The more the actors maintain relationships with each other, the more they will exchange and coordinate with each other, and conversely, the less they will do so with those who are further away. Intra-group coherence and convergence (“policy work”) is assumed from the relationships (Fisher et al., 2013).</p>	
Algorithm	General Operation
<p>Hierarchical algorithm with 4 different settings: Euclidean distance/Complete linkage (hclust_ec); Euclidean distance/Ward (hclust_ew); Manhattan distance/Complete linkage (hclust_mc); Manhattan distance/Ward (hclust_mw).</p>	<p><i>The basic idea is to construct the hierarchical relationship among data in order to cluster. At the start, each data point stands for an individual cluster. The two clusters that are the closest neighbors are then merged into a new cluster until only one cluster remains. The concept of “neighborhood” depends on the distance between nodes, which is computed by squaring the Euclidean or Manhattan distances and grouping them into a symmetrical matrix. The clustering method (here, complete linkage and Ward’s algorithm) identifies the closest nodes to aggregate them. We obtain a hierarchical dendrogram which is cut to the desired number of clusters.</i></p>
Divisive methods	
<p>These algorithms essentially consist of removing the links connecting communities to each other. This identifies how efficiently the network can be divided into disconnected pieces, provides the underlying community structure of the network, and describes who is connecting the communities. This information can be useful in understanding how and to what extent transmissions can be interrupted within a network (Smith et al., 2020).</p>	
Algorithm	General Operation
<p>Edge betweenness (Girvan and Newman, 2002)</p>	<p><i>At each iteration, the betweenness centrality (Freeman, 1979) of all the links is calculated and the edges that have a high likelihood of linking separate communities are removed until all the vertices are isolated. A dendrogram of the graph is thus obtained. The algorithm then returns the partitioning that maximizes the modularity score.</i></p>
<p>Minimum cut</p>	<p><i>The minimum cut of a graph is the minimum number of edges or the minimum total weight of edges in the case of links with values that must be removed to separate the graph into two components.</i></p>
Optimization based	
<p>The label propagation algorithm models the adoption of social norms or beliefs because it defines communities based on iterative adoption processes. However, it focuses on the adoption that occurs when the majority of nodes adjacent to a specific node are in the same community. In the ACF field, this algorithm family has recently been used for the classification of actors based on latent characteristics such as shared beliefs (Khvatsky et al., 2020).</p>	
Algorithm	General Operation
<p>Label propagation (Raghavan et al., 2007)</p>	<p><i>Initially, a unique label (community) is assigned to each node. At each iteration of label propagation, each node adopts the label shared by the majority of its neighbors until an equilibrium is reached, i.e. once each node has the same label as the majority of its neighbors. Therefore, label propagation can be considered as a local optimization method aimed at maximizing the number of neighbors having the same label.</i></p>
Optimization based on modularity	
<p>In the network approach, the observation of a relationship between actors is made by the presence or absence of a link between them (and its strength in the case of valued networks). The notion of intra- and inter-group density is at the heart of ACF approaches postulating that like-minded actors tend to coordinate their actions while these interactions are reduced between actors with different points of view. The higher the density in the clique, the more frequent and present the exchanges. At the same time, the lower the inter-clique density (isolation), the more likely it is that the political work of coordination (alignment of core and representations) takes place within the clique. There is a convergence here with homophily approaches (Weible and Sabatier, 2005; Metz et al., 2021; Satoh et al., 2021; Kammerer and Ingold, 2021b).</p>	
Algorithm	General Operation
<p>Random walks/Walktrap algorithm (Pons and Latapy, 2005) (walktrap)</p>	<p><i>The distance between vertices is measured by random walks in the network. The basic intuition of the algorithm is that random walks in a network tend to be trapped in densely connected parts corresponding to communities. Walktrap uses the result of the random walks to merge the separated nodes into communities in a bottom-up manner. A tree is obtained and the partition chosen is that which maximizes modularity.</i></p>
<p>Fastgreedy algorithm (Clauset et al., 2004) (fastgreedy)</p>	<p><i>This is a hierarchical agglomerative method based on a modularity criterion. Initially, the nodes are divided into distinct communities, each vertex being a community. The algorithm operates by finding the difference in modularity that would result from the amalgamation of each pair of communities, and by merging the pairs that increase the modularity to the greatest extent. This operation is repeated until no merging of community pairs leads to an increase in modularity.</i></p>
<p>Spectral/Leading eigen algorithm (Newman, 2006)</p>	<p><i>This method performs a spectral optimization of modularity by conducting an eigen-decomposition of the modularity matrix $B = A - P$, where A is the adjacency matrix of the network and P contains the probabilities that a link exists between each vertex in a random network in which the degrees of all vertices are the same as in the input graph. Community membership is then inferred by computing the eigenvector of the modularity matrix for the largest positive eigenvalue, and then separating the vertices into two communities based on the sign of the corresponding element in the eigenvector. The elements of the main eigenvector of the modularity matrix measure the degree to which the vertices belong to each of our two communities.</i></p>
<p>Louvain/Multilevel algorithm (Blondel et al., 2008) (louvain)</p>	<p><i>The Louvain algorithm (or Multilevel algorithm) is a greedy approach that optimizes modularity. Initially, the algorithm assigns a different community to each node in the network. For each node, it considers the neighbors and evaluates the modularity gain by removing the node from the current community and placing it in the neighbor’s community. It will be placed there if the gain is positive and maximized, otherwise, it will remain in the same community. This process is applied repeatedly and for all nodes until there is no more improvement, i.e. when a local maximum of modularity is obtained. Then, the algorithm builds a new network whose vertices are the communities identified in the first phase. The first phase is re-applied to the resulting network. These steps are repeated until there are no more changes in the network and maximum modularity is achieved.</i></p>
<p>Spinglass algorithm (Reichardt and Bornholdt, 2006) (spinglass)</p>	<p><i>Each vertex is characterized by a spin with q possible values, determining the maximum number of clusters allowed. The algorithm optimizes a function that rewards links within a community and penalizes those between communities. The principle is that edges should connect nodes of the same spin state (community), whereas nodes of different states (different communities) should be disconnected. It is possible to parameterize the function to favor internal links to a greater or lesser extent.</i></p>

(continued on next page)

Table 1 (continued).

Partitioning based on block models	
Block modeling algorithms compose communities of nodes with similar properties, i.e., they have similar connection patterns with other vertices, and thus similar neighbors (Borgatti and Grosser, 2015). This feature is prevalent in the ACF literature and implies the emergence of cooperation between actors occupying similar positions in the network. Indeed, to the extent that the characteristics of nodes are shaped by their social environment, we expect structurally equivalent nodes to develop similar characteristics such as beliefs and attitudes or political affiliation (Adam and Kriesi, 2007; Howlett et al., 2018).	
Algorithm	General Operation
CONCOR (Breiger et al., 1975) using <code>concoR</code> package (Suda and Traxler, 2020) (<code>concor_algo</code>), and using the function <code>CONCOR</code> (<code>concor_fct</code>) ^a	<i>The CONCOR method measures structural equivalence using correlation. That is, it measures the similarity between vertices based on the pattern of their relations to identify structurally equivalent nodes by correlating their sets of relations. This allows us to produce a block model of several relations simultaneously. The method is a hierarchical clustering algorithm that divides the network into two, after which the operation can be repeated on the sub-networks.</i>
Tabu Search (Glover, 1989; Glover and Laguna, 1997; Brusco and Doreian, 2019; Doreian et al., 2005) using Pearson correlation (<code>tabu_links</code>) and Euclidian distance (<code>tabu_dist</code>). ^b	<i>Tabu Search starts with a random vertex in the network and tries to reach the local minimum near this point. Once the local search step is complete, it stores the best point found in the “Tabu list” and repeats the search process with a new random point. The Tabu list prevents the algorithm from choosing the same point twice. To perform this local search, the algorithm takes the initial solution as the current solution and then generates its neighborhood by applying a set of different operations or inverse moves. It chooses the best solution to be the next current solution or stops if the solution cannot be improved. The selection method can be either the first improvement (selects the first solution in the neighborhood that is better than the current solution) or the best improvement (has to compute the objective function for all candidates in the neighborhood and selects the best one). The stopping criterion is usually defined by reaching a maximum iteration limit. As a final solution, the best solution among all visited solutions will be returned.</i>

^a Note that for our case study, we test both the Concor algorithm available in the `concoR` package on RStudio but also the Concor function as described by Breiger et al. (1975) as we noticed that the results differ and, in the absence of knowledge about real communities, we cannot make a justified choice. For the function, we first form a square correlation matrix between each pair of actors based on their links. Each row of this actor-by-actor correlation matrix is then extracted and correlated with each other row. Eventually, the elements of this “iterated correlation matrix” converge to a value of +1 or -1. We then split the data into two sets based on these values to form a two-block solution. We can then run the same process on each of the blocks to form a 4-block solution and so on up to the desired number of blocks. In our situation, to be consistent with the average number of communities found by other algorithms, we stop at 2 blocks.

^b Note that we run the Tabu Search algorithm on two different matrices. Indeed, the indirect measures of structural equivalence most used in network analysis seem to be Pearson correlations; allowing us to identify similar link profiles (which we apply to the adjacent matrix of the network), and Euclidean distances measuring the dissimilarity between the link profiles of each pair of actors (which we apply to the matrix of Euclidean distances between the actors in the network).

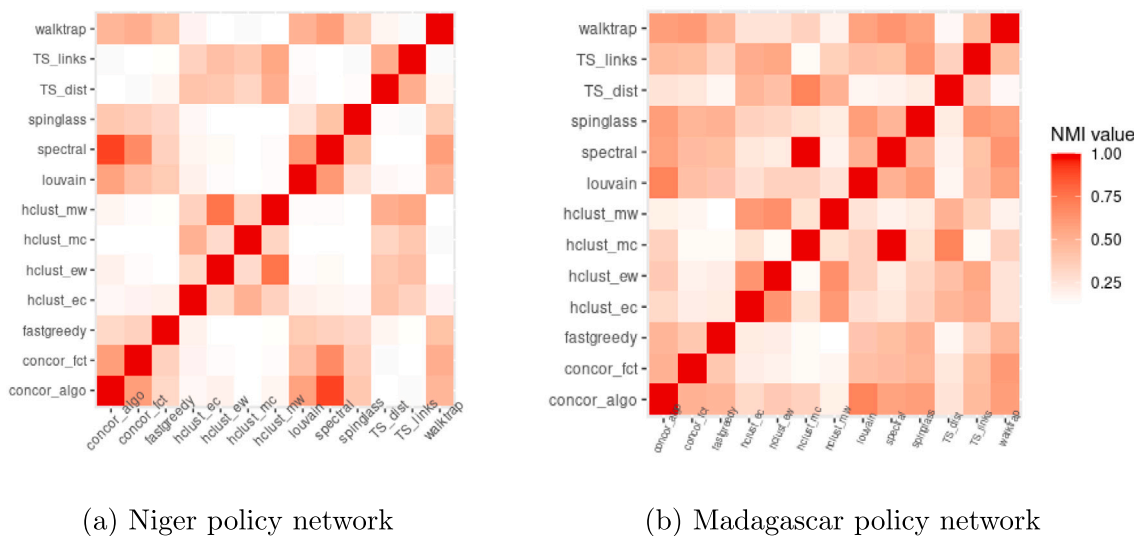


Fig. 3. Normalized mutual information matrices.

When applied to the Madagascar data, Walktrap maximizes the convergence indicator, although it narrowly precedes Spinglass (Table 2(b)). Although the Walktrap algorithm presents strong heterogeneity, while its competitors may present better results regarding this criterion, it produces the partitioning that presents the most robust convergence from all the others. The result of the best clustering partition can be visualized, and, in this case, we have three cliques in the graph (Fig. 4(b)).

Applied to our two sets of real-world data, which have the characteristics of policy networks (reduced number of nodes, relatively high density) while being structurally different (different number of vertices, links, and clusters), the community detection methods identify clusters

whose composition differs, sometimes to a great extent. According to our performance indicator, the algorithm whose results converge the most on all of them, which maximizes the criteria of possible advocacy coalition formation, is the Spectral algorithm in Niger’s case and the Walktrap algorithm in Madagascar’s case.

The convergence indicator is much weaker in the case of Niger, a network in which we recorded missing responses, which had strong implications for cluster composition, underlining, in particular, the sensitivities of hierarchical algorithms and those based on structural equivalence. These results highlight the problem posed by missing data and the attention the researcher must pay to it. - These results are aligned with the recent use of the Walktrap algorithm (Kammerer

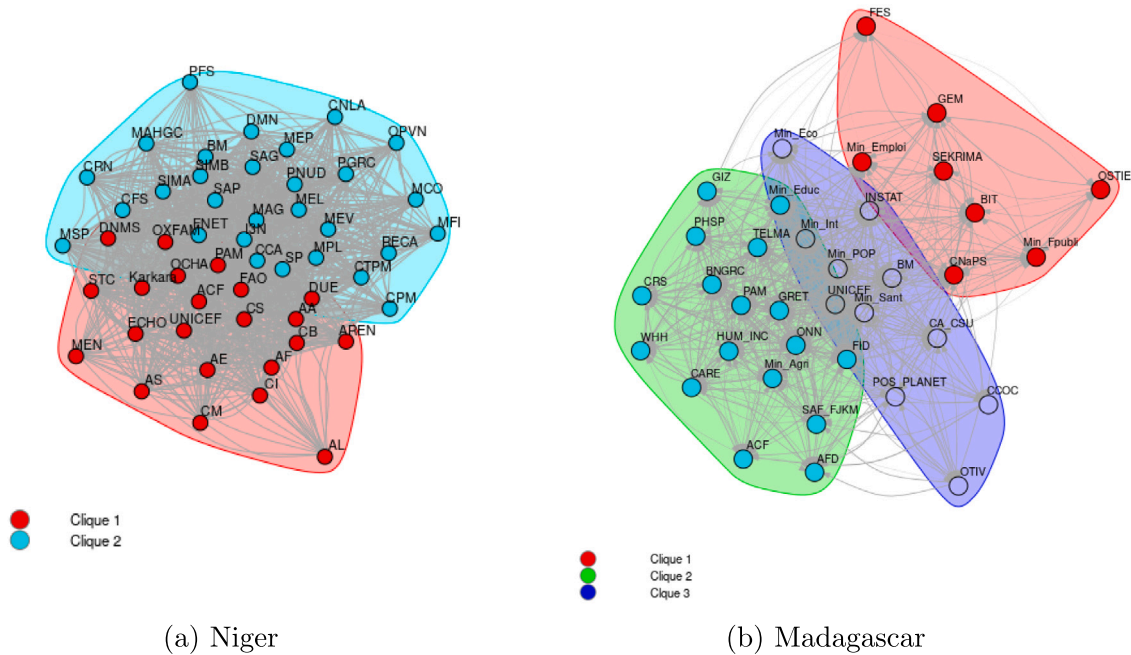


Fig. 4. Visualization of cliques in each network.

Table 2
Ranking of policy network algorithms based on the performance indicator.

	M_{NMI}^a	H_{NMI}^a	I_{NMI}^a
spectral	0.33	0.34	0.21
concor_algo	0.31	0.31	0.21
walktrap	0.27	0.24	0.21
concor_fct	0.27	0.26	0.20
louvain	0.26	0.25	0.20
hclust_ec	0.22	0.15	0.18
hclust_mw	0.25	0.26	0.18
TS_dist	0.22	0.20	0.18
TS_links	0.22	0.21	0.17
fastgreedy	0.20	0.15	0.17
hclust_ew	0.22	0.22	0.17
spinglass	0.20	0.16	0.17
hclust_mc	0.18	0.16	0.15

(a) Niger

	M_{NMI}^a	H_{NMI}^a	I_{NMI}^a
walktrap	0.47	0.30	0.33
spinglass	0.40	0.19	0.33
hclust_mc	0.46	0.32	0.31
TS_links	0.42	0.27	0.31
louvain	0.41	0.27	0.30
hclust_ew	0.35	0.14	0.30
fastgreedy	0.35	0.17	0.29
concor_algo	0.40	0.28	0.29
concor_fct	0.39	0.29	0.28
spectral	0.35	0.22	0.28
hclust_ec	0.26	0.19	0.21
hclust_mw	0.25	0.19	0.20
TS_dist	0.17	0.13	0.14

(b) Madagascar

4.2. Perform a robustness test to check the number of clusters selected

In the case of Niger, this question does not arise because the algorithm which maximizes our performance indicator, Spectral, also known as Leading-Eigen community detection, belongs to the family of algorithms whose operation maximizes modularity and, therefore, only proposes a single partition which automatically proposes a fixed number of communities. Hence, we cannot set parameters for this element, and we will keep the proposed number of communities (i.e. $k = 2$).

Regarding the Madagascar network, the Walktrap algorithm offers the possibility of setting the “path length” of the algorithm, which can impact the number of communities proposed by the algorithm. We therefore test for a path length ranging from 1 to 10 steps (t). There is no need to test for more than this, as the results are redundant from 6 steps upwards. The modularity is maximized for $t=1$ ($\text{mod} = 0.098$). Or “the number of steps in each random walk is a key hyperparameter of the algorithm: choosing a very small value will mean that walks may not be able to reach some of the nodes within their own community, while choosing a very large value will make it more difficult to differentiate between communities” Ballal et al. (2022, p. 20). In addition, the use of a single movement in a Random Walk algorithm for community detection is generally not recommended since it essentially reduces to a random jump from an initial node to a neighboring node, leading in particular to a lack of representativeness (the random walk only captures a very limited portion of the network) and instability of the results (a single random walk is highly dependent on the starting node). In our case, we find a partition into 4 clusters, one of which comprises a single actor. We, therefore, exclude this result and look for the second-best modularity. In the second place, we find $\text{mod} = 0.097$ for $t = 3$ and $t = 5$, which provide the same partitioning within 3 communities. It confirms the result we found in the previous step.

For both networks, the robustness test that we carry out to check that the number of communities initially defined is indeed the one that maximizes the optimization indicator associated with the algorithm selected and does not change the previous results. However, since these were algorithms from the modular family, this step may be more

and Ingold, 2021a) in the policy network coalition framework, an algorithm that has been chosen for its performance over 12 others. - The competitive algorithms in both cases appear to be mostly from the Modularity optimization family (Spectral, Walktrap, Spinglass).

relevant in the case of other algorithm families that maximize the convergence indicator since the latter requires manual parameterization of the number of communities.

4.3. How much these results are relevant in both cases?

In Niger (Fig. 4(a)), the results presented above appear consistent with our observation of the DNP-GCA structure where national and international organizations are separated, defining the area of the political negotiation framework. Indeed, the first clique combines the majority of the international and external actors, several emergency and food crisis management organizations (PAM, UNICEF, FAO) but also public multi- or bi-lateral institutions (French embassy, European Union Delegation). Regarding the centrality indicators, this clique consists of the dominant international coalition made up of donors to food crisis management. Aggregating the most powerful political organizations in terms of resources and financial contributions, this clique is based on emergency interventions against circumstantial crises due to exogenous shocks; sometimes, they act outside the national system because of pre-existing mistrust. These organizations observe natural, climatic, agricultural, etc., risks that produce food insecurity for individuals, but they act without a long-term vision or forecasts of the development of local capacities to provide a more structural answer to the annual food crises. Clique 2 represents the national coalition with the majority of ministries and national actors like DNP-GCA organizations (agriculture ministry, ministry for livestock, permanent secretary, CCA, CNLA, OPVN). This clique is affected by a “dependence disease” from aggregating organizations: they face crucial lack of resources and thus they need funds from international donors, but they also express criticism of the power, influence and dominance of these international organizations. Some powerful national institutions (e.g. the MAG) promote a more holistic vision of the structural requirements in order to achieve productive, sustainable development in Niger. However, regarding their donors’ dependence, they do not act in this way and frequently, they act in line with the international organizations.

In Madagascar (Fig. 4(b)), we observe another case with more transnational groups. The first clique is made up of thirteen actors, including the leading trio of UNICEF, MPPSPF, and the Ministry of Health (Fig. A.4), plus several emergency and international organizations (like the World Bank, BM). It is also characterized by the strong presence of public institutional actors, with only one private sector actor and the FID as the only international NGO. This clique presents a local expression of the strength of the internationally dominant social protection coalition based on refining and broadening “government targeted at the poor” towards the management of social, but also natural, climatic, agricultural, etc. risks that cause economic insecurity for individuals. This individualized and security-oriented approach to social protection is mainly implemented through a non-contributory, assistance-based system, known as cash-transfer. The composition of Clique 1 confirms this characterization. It includes UNICEF, the international organization leading the way on this vision of social protection in the country, and the MPPSPF, which supports this approach and, therefore, seeks to focus solely on the non-contributory scheme. Clique 2 represents one of the two competing visions at the international level, one the ILO has supported in particular from the outset. In this approach to social protection, the focus is more on enforceable social rights and how they can be extended and activated through contributory schemes and insurance mechanisms linked to work and employment in all its forms. This is reflected in the composition of Clique 2, which includes the ILO, the CNAPS, trade unions and employers’ organizations, as well as the Ministry of Labor, all of which, historically, have had this view of social protection. Clique 3, the last one, is institutionally more heterogeneous than Cliques 1 and 2, integrating marginal actors in the policy network. It is more oriented towards development activities. This third clique

brings together bilateral and international “second rank” donors such as the PAM, AFD and GIZ, who are less involved in the social protection field, international NGOs, national government actors, and Malagasy associations.

4.4. Robustness checks

Policy Network data collection often involves respondents who fail to respond. Whether actors provide no information about any ties to other members of the network or fail to mention specific ties, the network analysis must be able to deal with invalid data. In such cases, the researcher is given three options: (i) use a complete case analysis, (ii) use an available case analysis, or (iii) impute data values to replace missing data. Although we initially opted for an available case analysis as it allows us to include all network actors in the analysis, keeping non-respondents in the network can lead to biased results, as it means imputing a null value to links from non-respondents to all network actors, a method known to be the worst treatment for obtaining blockmodel structures of both binary and valued networks (Znidarsic et al., 2012; Znidarsic et al., 2017). Other methods also have their disadvantages. Indeed, applying the complete case analysis method, i.e., removing non-respondents from the network, is a strategy that compromises the macro-structure analyses via block modeling as well as the micro-structure analyses of all members of the network, including non-respondents (Znidarsic et al., 2019). When it comes to data imputation, this can lead to results that are more or less distant from the real data, depending on the method selected. To evaluate our performance indicator in the case where actors fail to provide data, we apply the method to the Niger network, first with the complete-case analysis and second where the missing values are imputed.

For the Niger data, eight actors failed to respond during data collection, giving a relational response rate of 84%.¹⁴ We withdraw or impute the outgoing ties of these actors and then perform the last three steps of the partitioning selection method. We do not perform the first two steps, which consist of refining algorithm selection, in order to keep the same selection and make the results directly comparable.

First, we perform the complete case analysis. The partitioning of Niger’s network without non-respondent actors shows a stronger overall convergence which is even more pronounced among algorithms belonging to the same families, together with a fairly pronounced heterogeneity towards the hierarchical algorithms (Fig. 5(a)).

Znidarsic et al. (2012, 2017) and Znidarsic et al. (2019) stress that available information from respondents to non-respondents, their incoming ties, can be used to support the imputation of data for non-respondents. We choose to apply the imputation treatment of the median of the three nearest neighbors based on incoming ties (3-NN)¹⁵ which treats non-respondents individually (and not as a group) and as the treatment for which the imputed values are closest to what they could be. We obtain a matrix of NMIs a little closer to what we had with the non-respondents (Fig. 3(a)). The differences are mainly in the hierarchical methods which group the non-respondents into a single cluster, forming a strong consensus of their own.

In the case where we withdraw the missing values, the indicator shows that the partition of the Louvain algorithm maximizes the consensus with the other community selection methods. When a missing values treatment is applied, in our case the k-NN method, it is the

¹⁴ Considering m as the number of non-response actors and n the total number of actors, the relational response rate is $1 - m/n$.

¹⁵ The Euclidean distances between the actors are computed based on their incoming links. For each non-respondent, the three nearest neighbors are selected using the smallest calculated Euclidean distance. For each missing outgoing link v_{ij} of the non-respondent i , the median of the values of the corresponding outgoing links of the three closest actors is computed. Finally, this value is imputed for the missing link.

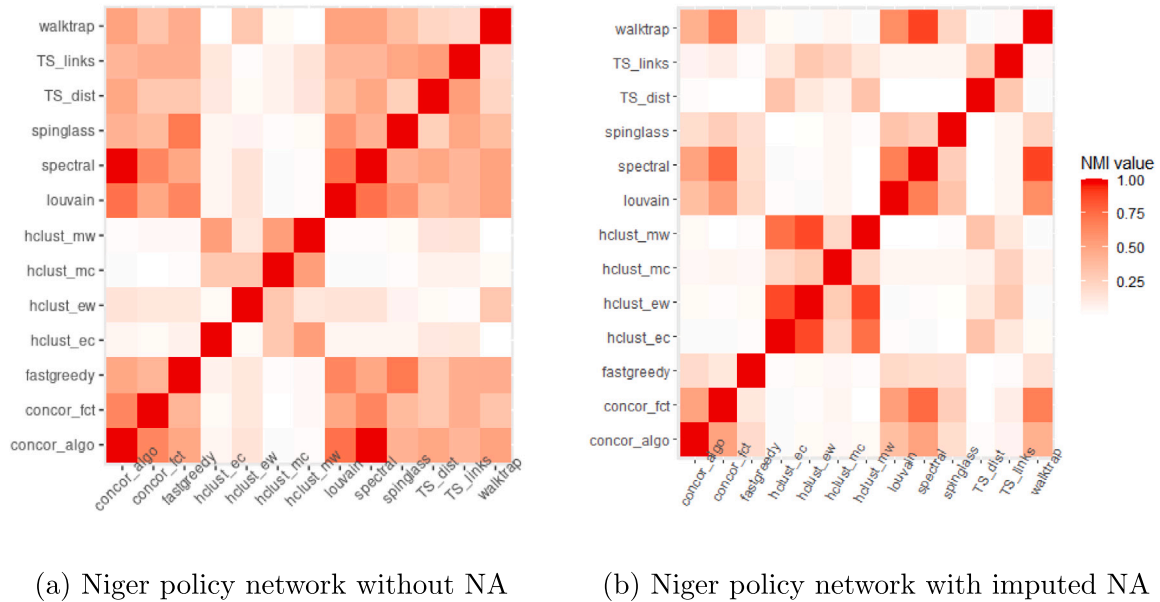


Fig. 5. Normalized mutual information matrices.

Table 3
Niger Policy Network algorithm ranking based on the performance indicator.

	M_{NMI}^a	H_{NMI}^a	I_{NMI}^a
louvain	0.43	0.32	0.29
spectral	0.45	0.36	0.29
concor_algo	0.45	0.36	0.29
fastgreedy	0.40	0.28	0.29
TS_links	0.36	0.21	0.28
concor_fct	0.37	0.27	0.27
spinglass	0.37	0.27	0.27
TS_dist	0.33	0.20	0.26
walktrap	0.34	0.23	0.26
hclust_ew	0.20	0.11	0.17
hclust_mw	0.20	0.18	0.16
hclust_ec	0.18	0.14	0.16
hclust_mc	0.18	0.17	0.15

(a) Without missing data

	M_{NMI}^a	H_{NMI}^a	I_{NMI}^a
spectral	0.34	0.37	0.21
concor_fct	0.31	0.32	0.21
louvain	0.29	0.29	0.21
walktrap	0.32	0.34	0.21
concor_algo	0.26	0.23	0.20
hclust_ew	0.27	0.32	0.18
hclust_ec	0.26	0.30	0.18
hclust_mw	0.26	0.30	0.18
spinglass	0.20	0.14	0.17
TS_links	0.19	0.12	0.17
hclust_mc	0.18	0.10	0.16
fastgreedy	0.16	0.09	0.15
TS_dist	0.17	0.14	0.14

(b) With imputed missing data

Spectral algorithm that maximizes the indicator (Table 3(a)).¹⁶ As the selected algorithms propose the best number of clusters from the outset, it will not be necessary to perform the 5th step in those cases.

5. Conclusion and implications for further research

Our paper provides a new and original strategy from the perspective of coordinated action in ACF, a 5-Steps selection method to answer the fundamental question about the identification of clusters or subsystems from specific and contextual policy networks in order to identify advocacy coalitions. Tested on two real African policy processes in different policy sectors, our results demonstrate the importance of integrating BMCD strategies into the policy process research. This new method and its applications in this paper need more replications in different contexts of policy processes and their stages. It would also be highly appropriate in the context of ACF to replicate and test this exercise on belief proximity networks, as seen in Henry et al.’s work (Henry et al., 2011). Even consider an extension for bi-modal networks by including tools from discourse network analysis (DNA) in order to identify clusters and coalitions based on the support for or rejections of beliefs concerning a specific policy issue (Kammerer and Ingold, 2023; Markard et al., 2016-03). Indeed, we believe that this method could be helpful for the part of the ACF literature that mobilizes belief networks or their proxy and greatly encourages future work in this direction.

First, the density and the size of the policy network matter a lot and can affect the identification process. Both of the real policy networks used are denser than simulated networks outside the policy process literature. It is not original regarding the crucial goal in both policy processes we studied: organizing inter-organizational collaboration to develop a common vision and strategy. For this reason, the relevant set of algorithms for such applications is not exactly the same as those traditionally used in BMCD studies. We excluded the “optimal cluster” algorithm from our selection because, although it was presented as performing well among the community detection methods, the calculation

¹⁶ The differentiation of algorithms at the top of the list is once again made from the third decimal place.

time appeared to be extremely long (still no results after one hour), and the results are not relevant because of the high network density.

Second, our 5-Step method application demonstrates that the “best algorithm” can be rigorously determined in a specific context of policy process by our novel performance indicator (I_{NMI}^a) maximizing two fundamental components based on NMIs ($M_{NMI}^a \times H_{NMI}^a$). The most judicious approach is to find the best balance between convergence with all selected algorithm partitions (M_{NMI}^a) and homogeneity with each of the other algorithms regarding their respective NMIs (H_{NMI}^a). The main limits of the performance indicator reside in the limits of the algorithms used. On the one hand, we still need to determine the number of clusters, which is one of the consequences of the algorithmic methods used in ACF. Nevertheless, if the correct number of clusters q is known or discovered and the optimization is constrained on the subset of partitions with q clusters, these algorithms can prove to be competitive. This is an area where we prove that the performance indicator provides support by determining the most competitive of them, while the NMI calculation phase allows the presence of different numbers of clusters.

Furthermore, it appears that algorithms optimizing modularity seem the most relevant regardless of the data or their structure (with or without missing values). Although this result cannot be generalized with our work, it nevertheless seems to confirm the recent interest in the literature for using this family of algorithms in ACF to capture cliques in policy networks (Kammerer and Ingold, 2021b).

Collecting complete data on policy networks is often difficult, and missing values are frequent. The robustness tests we carried out to check the sensitivity of several algorithms when treating missing values show that even when the values are imputed, algorithms can bring them together in the same cluster. In the case where the majority of the selected algorithms are sensitive to missing values, the indicator will lead to the selection of a partition in which this bias is present. In other words, ACF researchers must be careful with missing data; it affects the results, and imputation methods do not solve the problem. Future ACF studies using network analysis need to report missing nodes and indicate precisely how they will deal with the problem (drop, include or impute).

It should be noted that the alignment of policy convictions within the groups identified enables us to distinguish a community of actors in the structural sense of the term from an advocacy coalition in the ACF perspective. Hence the previous recommendation for future replications on belief proximity networks. However, this paper solves an important methodological issue concerning the identification of political subsystems from a network perspective, based on coordination between actors. Without any empirical consideration of actor policy beliefs in this paper, we do not pretend that this new tool is sufficient to determine the policy coalitions like ACF tradition (Weible and Sabatier, 2005). Although our method has so far only been applied to collaboration and information exchange networks, it has the potential to be applied much more widely. Researchers could extend this analysis to the links that seem most relevant to their research question and context. The literature examining how beliefs and relationships are aligned in a network highlights the complexity of this task, particularly given the interdependence for access to resources, the search for influence and the management of conflicts within the network (Henry, 2011; Howe et al., 2021). Therefore, applying our method to multiple relationship networks that superimpose several types of links, such as collaboration, exchange of resources, trust, or a mapping of beliefs, would be interesting. This broader approach would enable us to better understand the dynamics of governance networks and to develop more sophisticated analytical tools for exploring their structures and implications in various research contexts.

Finally, the Advocacy coalition literature highlights that the growing number of actors involved in decision-making processes makes it difficult for them to be autonomous, and they have to manage both their interdependence over resources and their conflict over ideas

(Weible, 2005). The governance network can thus be a useful analytical concept for understanding the configuration of actors involved in a political sector, its changes during the policy process and the circulation of ideas and resources. In policy process theory, particularly in the advocacy coalition framework, the choice of actors concerning all interactions is largely based on ideological similarities. In order to transform these shared beliefs into public policy, cooperation is essential and will produce a structural rapprochement between socially dependent actors. The causal relationship between homophily and interactions appears particularly relevant in governance networks engaged in controversial political processes. In more moderate political contexts, it may appear subordinate to relationships of trust, power and influence, as suggested by Jenkins-Smith and Sabatier (1994) and Henry et al. (2011). The causality of homophily on relationships may not be obvious if we consider that learning and convergence to an agreement can occur in frameworks of repeated interaction, even in the presence of contradictory belief systems (Ostrom, 2005). Numerous factors can play a part in the formation of relationships between players, from the existence of pre-existing relationships to structural equivalence, resource dependency or the degree of power (Marsden and Friedkin, 1993; Coleman, 1990; Burt, 2000). A number of studies in the social network analysis literature stress the importance of network structure in the formation of collective beliefs. To some extent, the discussion revolves around a “chicken-and-egg” debate: when is social capital the source of ideological rapprochement, and when is it ideological similarity that underpins collaboration? This is a fundamental theoretical issue crossing ACF and network analysis that, unfortunately, goes beyond the scope of this article, which focuses on proposing a methodological approach for robust identification of actor subsystems based on coordination interactions. However, it would be interesting to develop this question in future research.

CRediT authorship contribution statement

Thibaud Deguilhem: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Juliette Schlegel:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jean-Philippe Berrou:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Ousmane Djibo:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Alain Piveteau:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

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Appendix

See Figs. A.1–A.4 and Tables A.1 and A.2.

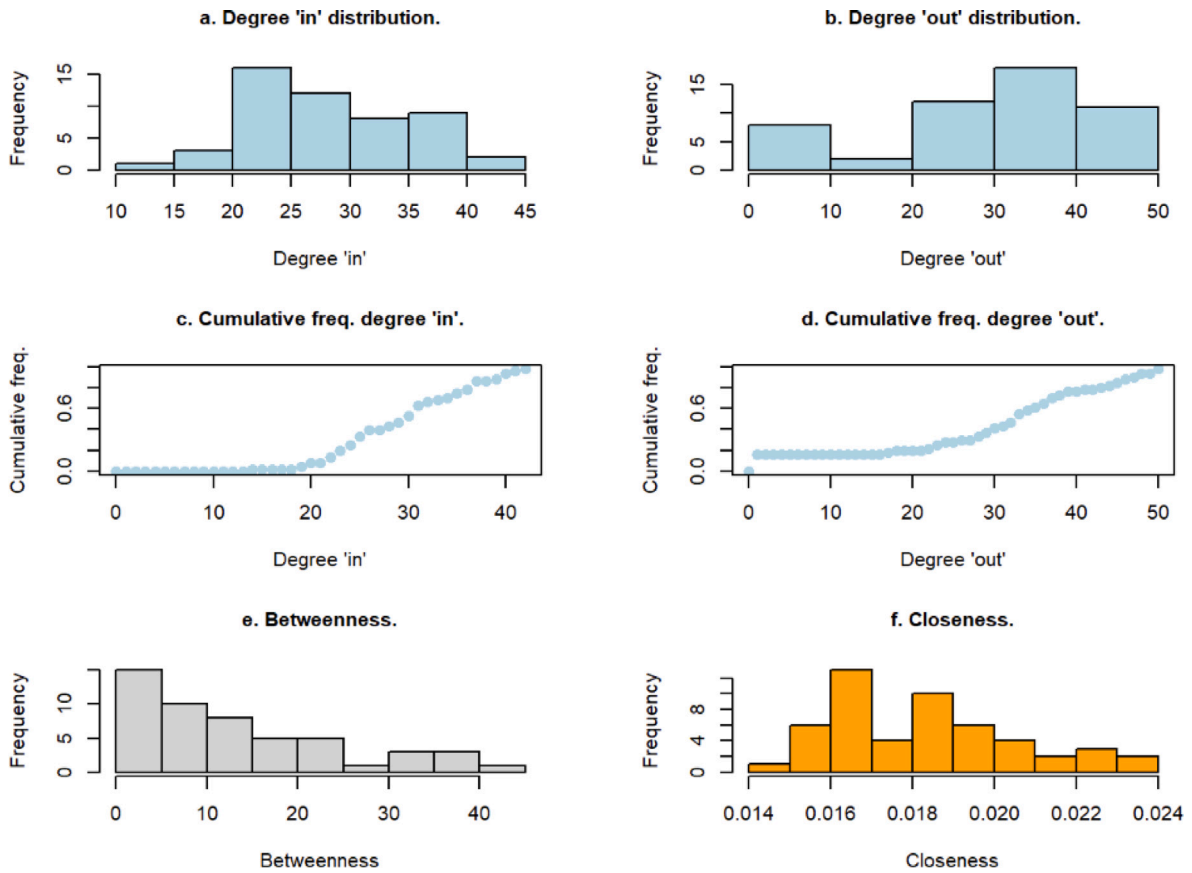


Fig. A.1. Niger's dispositive sharing information network (descriptive statistics).

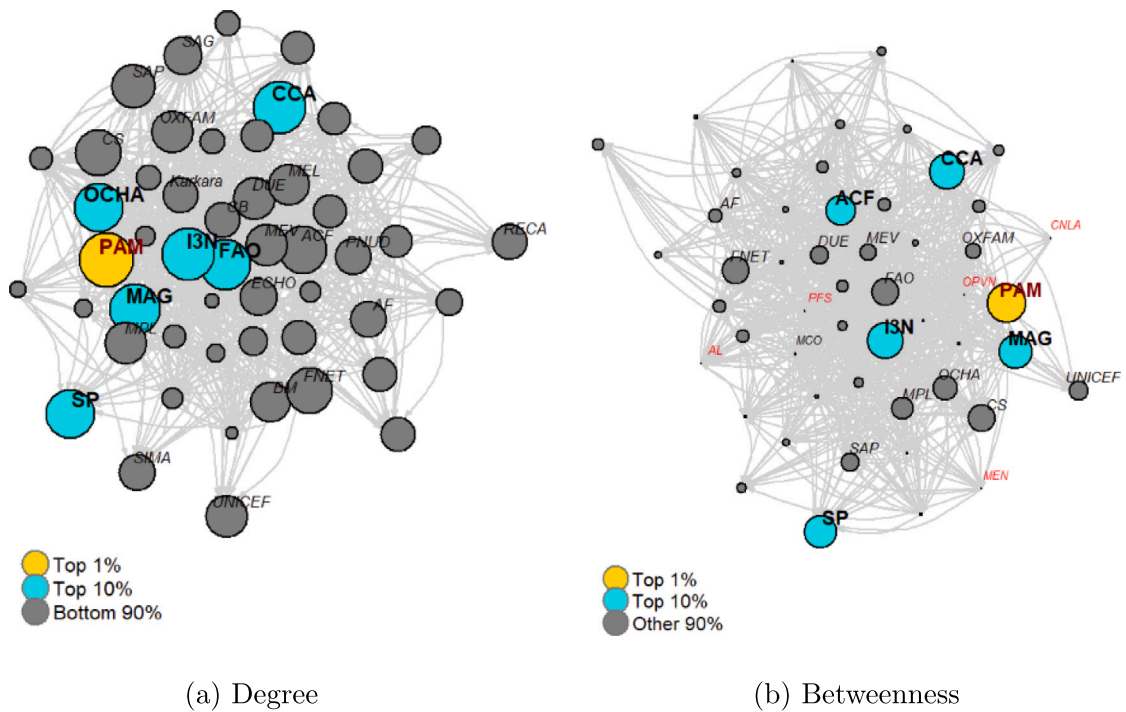


Fig. A.2. Central nodes in Niger's food crisis prevention and management policy network (sharing information). *Notes: the graph visualizes only the highest link strength ($s_{ij} > 2$). nodes' labels are assigned only to nodes with a degree or a betweenness higher than the network average and to the 10% nodes with the lesser betweenness (in red). Moreover, blue nodes (in bold) represent the top 10% in terms of degree or betweenness and golden nodes represent their top 1%. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)*

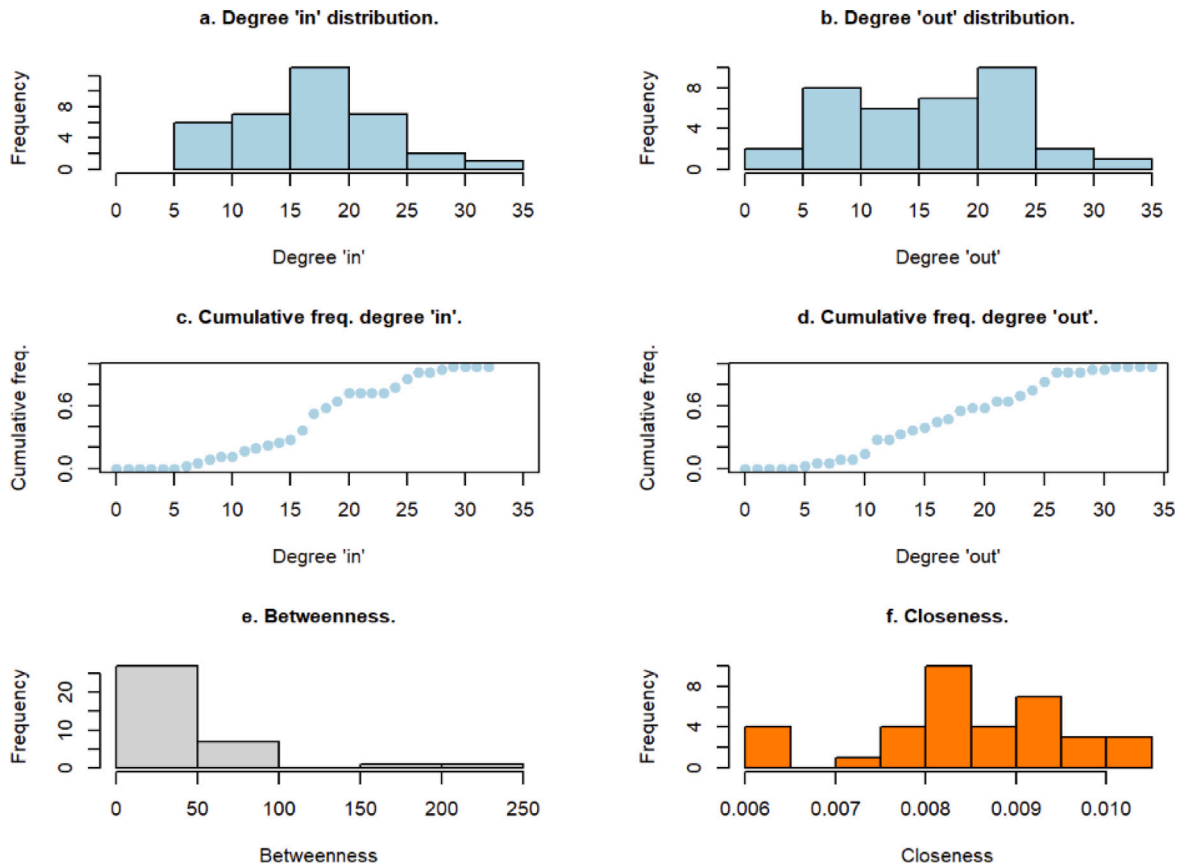


Fig. A.3. Collaboration Madagascar's social protection policy network (descriptive statistics).

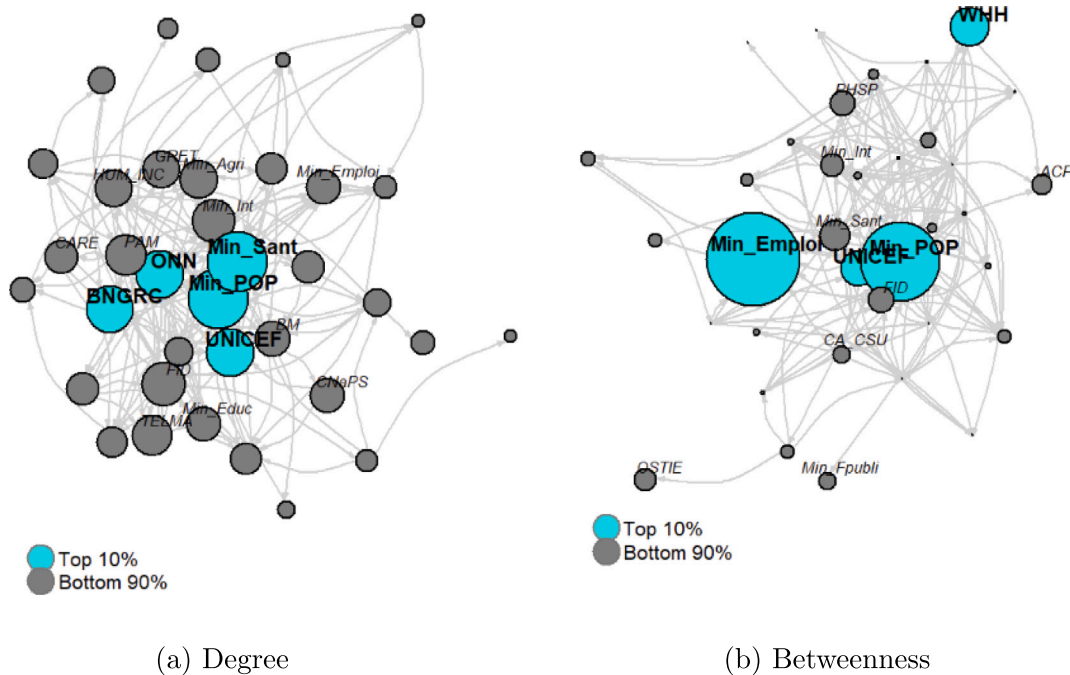


Fig. A.4. Central nodes in Madagascar's social protection policy network (collaboration). Notes: the graph visualizes only the highest link strength ($s_{ij} > 4$). nodes' labels are assigned only to nodes with a degree or a betweenness higher than the network average. Moreover, blue nodes (in bold) represent the top 10% in terms of degree or betweenness. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table A.1

Niger's social protection policy network: organizations' list.

Note: missing organizations are in *italic*.

Government (12)	
(CPM) <i>Prime Minister's Office</i>	(CTPM) Prime Minister's Technical Counselor
(MAG) Ministry of Agriculture	MCO <i>Ministry of Commerce</i>
(MAHGC) <i>Ministry of Humanitarian Action and Crisis Management</i>	MEL Ministry of Livestock
(MEP) Ministry of Employment and Social Protection	(MEN) <i>Ministry of Education</i>
(MEV) Ministry of Environment	(MFI) <i>Ministry of Financial</i>
(MPL) Ministry of Plan	(MSP) <i>Ministry of Public Health</i>
Government-related and DNP-GCA units (15)	
(CNLA) National Locust Control Center	(DMN) National Meteorological Department
(DNMS) Nutrition Department at the Ministry of Public Health	(OPVN) Food Products Office of Niger
(HCI3N) High Commission on the Initiative Nigeriens Feed	(CCA) Food Crises Unit (DNP-GCA)
(PFS) <i>Social Safety Nets Project</i>	(SAP) Early Warning System Unit (DNP-GCA)
(SP) Permanent Secretariat of DNP-GCA	(CFS) Social Safety Nets Unit (DNP-GCA)
(SIMA) Agricultural Market Information System	(SIMB) Livestock Market Information System
(RECA) National Network of House of Agriculture	(PGRC) Risk and Disaster Management Project
(SAG) Statistics of Agriculture Department	
International organizations (donors) (17)	
(UNICEF) UN International Children's Emergency Fund	(BM) World Bank (USAID - BHA)
(OCHA) UN Office for the Coordination of Humanitarian Affairs	(PAM) World Food Program
(ECHO) European Community Humanitarian Aid Office	(PNUD) UN Development Program
(DUE) Delegation of European Union	(FAO) Food and Agriculture Organizations of the UN
(AA) Germany Embassy	(AE) Spain Embassy
(CI) Italian Cooperation	(CM) Monaco Cooperation
(AF) France Embassy	(AL) <i>Luxembourg Embassy</i>
(AS) United States of America Embassy	(CB) Belgium Cooperation
(CS) Swiss Cooperation	(FNET) Famine Early Warning Systems Network
Civil society, NGOs, associations (6)	
(AREN) Association for the Revitalization of Livestock in Niger	(ACF) Action Against Hunger
(OXFAM) Oxford Committee for Famine Relief	(STC) Save The Children
(Karkara) Nigerien Association for the Dynamization of Local Initiatives	(CRN) <i>Nigerien Red Cross</i>

Table A.2

Madagascar's social protection policy network: organizations' list.

Government (8)	
(Min_POP) Ministry of Pop., Soc. Protection and Women	(Min_Eco) Ministry of Economy and Planning
(Min_Agri) Ministry of Agriculture and Animal Husbandry	(Min_Int) Ministry of Interior and Decentralization
(Min_Fpubli) Ministry of Civil Service, Adm. Reform, Labor and Social Laws	(Min_Educ) Ministry of Education
(Min_Emploi) Ministry of Employment, Technical and Vocational Education	(Min_Sant) Ministry of Health
Government-related (6)	
(CNaPS) National Reserve Fund of Social Protection	(ONN) National Office of Nutrition
(CA_CSU) Support Committee for Universal Social Security	(FID) Intervention Fund for Development
(BNGRC) National Office of Risk and Disaster Management	(INSTAT) National Institute of Statistics
International organizations (donors) (6)	
(UNICEF) United Nations International Children's Emergency Fund	(BM) World Bank
(GIZ) Gesellschaft für Internationale Zusammenarbeit	(PAM) World Food Programme
(ILO) International Labor Organization	(AFD) French Development Agency
Civil society, NGOs, associations (11)	
(CRS) Catholic Relief Service	(FES) Freidrich Eibert Stiftung
(GRET) Research and Technology Exchange Group	(HUM_INC) Humanity & Inclusion
(CCOC) collective citizens and civic organizations in Madagascar	(ACF) Action against Hunger
(SAF_FJKM) Jesus Christ Church Development in Madagascar	(POS_PLANET) Positive Planet
(SEKRIMA) Sendika Kristianina Malagasy	(WHH) Welthungerhilfe
Private sector (5)	
(TELMA) TELMA - telecommunications operator	(OTIV) National Network for Micro-finance
(PHSP) Humanitarian Platform of Private sector	(GEM) Malagasy Enterprise Union
(OSTIE) Antananarivo Inter-company health organization	

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