Chapter 3

A dynamic analysis of conflict networks in North and West Africa

Conflicts in North and West Africa are characterised by a high degree of complexity in which hundreds of rebel groups and violent extremist organisations are involved in a shifting series of alliances and rivalries with government forces and with each other. In order to map this complex conflict environment, this chapter develops a novel approach, known as dynamic social network analysis (DSNA) capable of modelling the creation and dissolution of ties, either positive or negative, among a violent group of actors over time. The DSNA approach relies on several metrics that show how co-operative and opposition networks evolve, change and adapt to foreign military interventions. The analysis of the evolution of conflict networks is conducted at the regional level (North and West Africa) and through three case studies (Mali and Central Sahel, Lake Chad, Libya). It leverages political event data from the Armed Conflict Location & Event Data Project (ACLED) that has catalogued violent extremist incidents in Africa since 1997.

KEY MESSAGES

- **Political violence is a relational process in which the structure underpinning the network of allies and foes provides constraints and opportunities for violent organisations.**
- **Relational approaches are well adapted to capture the complexity of contemporary conflicts due to their ability to represent and model networks of large numbers of actors that contain both positive and negative relations.**
- **Networks with positive ties convey more resources, ideas and knowledge than networks based on hatred, avoidance or conflict, which tend to aim at neutralising foes.**
- **The report introduces a dynamic approach to conflict networks to assess which violent organisations are the most structurally important and what the overall architecture of the conflict environment is in North and West Africa.**
- **The study also develops several simple metrics that measure how co-operation and opposition networks change over time, particularly with respect to foreign military interventions.**

A NETWORK APPROACH TO ALLIANCES AND RIVALRIES

This report adopts a formal analytical approach known as social network analysis (SNA) to map the changing relationships between government forces, rebels, violent organisations and civilians across North and West Africa. Unlike other social science approaches that might focus on the military strength or ideology of the belligerents, SNA assumes that political violence is a relational process in which the structure underpinning the network of allies and foes provides both constraints and opportunities for violent organisations.

Relational approaches such as SNA have been increasingly used since the early 2000s to model terrorist and criminal networks whose structure is often elusive and versatile (Krebs, 2002[1]; Pedahzur and Perliger, 2006[2]; Koschade, 2006[3]; Everton, 2012[4]; Zech and Gabbay, 2016[5]). It is only recently that formal approaches have been applied to Sub-Saharan Africa (Walther and Christopoulos, 2015[6]; African Networks Lab, 2020[7]). In North and West Africa, for example, actors in conflict form sparse and decentralised networks in which jihadist organisations such

Box 3.1
Clarifying terms

This report focuses on all forms of political violence in North and West Africa, including military attacks, rebellions, terrorism and communal violence. The term "**conflict**" used in the report refers to prolonged conditions of open fighting between groups, organisations or government forces without formal declarations of war or the possibility of an armistice. It describes a particular armed struggle, such as "the Malian conflict", or characterises warfare in general, as when the report discusses "actors in conflict" or a "conflict network". For this reason, conflicts differ from formal wars between states that typically have a clear beginning and end. In a region where inter-states wars are rare, the vast majority of the armed struggles studied in this report are conflicts rather than wars.

Several terms are used to describe the relationships, outcomes and structural properties that form a conflict network (Table 3.1). Positive relationships (or "ties" in the language of networks) between organisations are described as "**co-operation**", while negative ties are described as "**opposition**". The outcome of co-operative ties between groups is an "**alliance**", while the outcome of opposition ties is a "**rivalry**". In structural terms, alliances tend to reinforce the "**cohesion**" of the conflict network, whereas rivalries encourage "**fragmentation**".

Table 3.1
Various terms used for positive and negative ties, outcomes and properties

	Positive	Negative
Ties	Co-operation	Opposition
Outcome	Alliances	Rivalry
Structural properties	Cohesion	Fragmentation

Source: Authors.

as Al Qaeda in the Islamic Maghreb (AQIM) or Boko Haram occupy a prominent structural position due to their conflicts with civilian and government forces in several countries (Walther, Leuprecht and Skillicorn, 2018[8]). In Central Africa, recent research confirms that conflict networks are deeply embedded in the larger society. In the Democratic Republic of Congo, for example, demobilised combatants maintain extensive personal connections with many armed groups, blurring the distinction between covert and overt networks (Stys et al., 2019[9]).

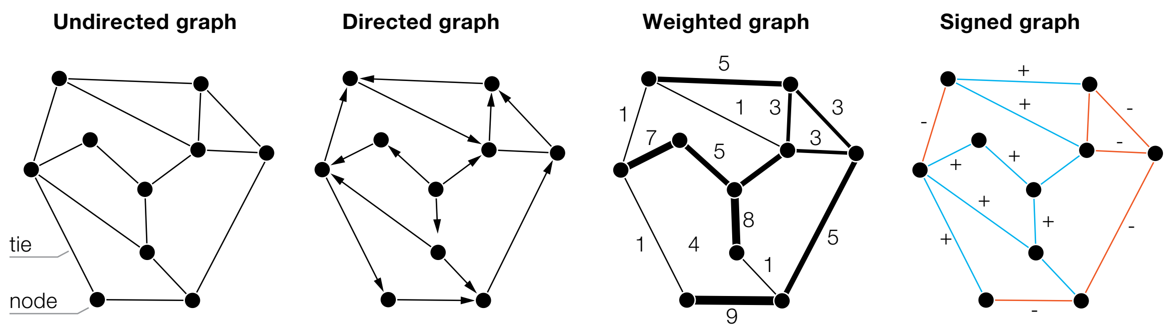
In East Africa, social networks contribute to explaining how violent groups emerge and lead to intergroup conflict (Box 3.1). Among the Nyangatom agro-pastoralists who live between South Sudan and Ethiopia, for example, violent raids to capture livestock are initiated by leaders who are particularly central in the network of raiders (Glowacki et al., 2016[10]). Other individuals are more likely to participate in intergroup violence if they are directly connected by friendship to a leader of a raid, suggesting that violence is affected by an individual's position in a social network. Similarly, studies conducted in Rwanda show that participation in genocidal violence is partly determined by the interpersonal networks in which individuals were embedded: individuals who are strongly connected through kinship or neighbourly ties are more likely to participate in killings than others (McDoom, 2014[11]).

Social network analysis

A social network is a set of individuals or groups that are connected to each other. Taken together, the collected set of actors and the relationships that connect them can be thought of as forming a network. In a basic sense then, social network analysis is the investigation of social patterns

Figure 3.1

Sociograms showing different ways to represent social ties between nodes



Source: Adapted from OECD/SWAC (2017[12]), *Cross-border Co-operation and Policy Networks in West Africa*, West African Studies, OECD Publishing, Paris, https://doi.org/10.1787/9789264265875-en.

through these networks. Accordingly, SNA has developed a set of distinctive theoretical perspectives. Chief among these is a focus on the relationships between actors rather than on the attributes of actors, such as age, gender or nationality, and an assumption that actors are interdependent rather than independent. SNA also argues that the structure of a social network impacts the choices and conduct of actors and that social networks have emergent effects that are more than the sum of their parts.

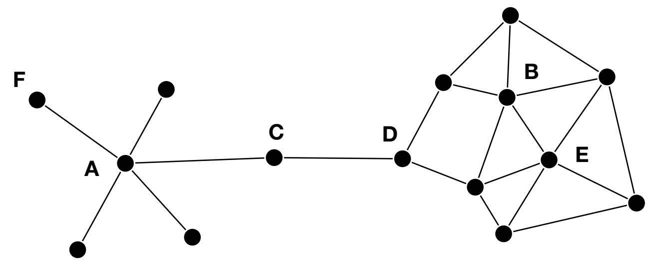
SNA has also developed distinctive concepts and associated terminology to support the investigation of social networks, which merit some mention here. For example, a social network is often represented visually with a specialised graph called a **sociogram** (Figure 3.1). In such graphs, each actor is a **node**, and the presence of a relationship is called a **tie**. A pair of nodes is known as a **dyad** and represents the smallest possible example of a network. However, a common level of analysis in a network is among **triads**, or groups of three nodes. Larger numbers of nodes can form a sub-community within a network, and these are typically referred to as a **clique**.

Because SNA emphasises relationships, the ties between nodes are important aspects of sociograms. Ties between actors can be **directed**, when the relationship involves some form of direction (sending and receiving information, for instance), or **undirected**, when the relationship does not imply directionality (such as friendship) or when the direction of the relations between actors is unknown. Networks can be **weighted** when the ties connecting actors have a value that varies in strength or intensity, or **unweighted** when only the presence or absence of a tie is represented. Finally, ties can represent positive relations, such as friendship or collaboration, or negative relations, such as opposition, avoidance or hatred. These **signed** networks are the main topic of this report (Figure 3.1).

Several concepts in SNA involve aspects of relations at the dyadic level. An important example between two actors is the idea of **reciprocity**, referring to a situation within which two actors acknowledge that they are engaged in mutual interaction. Reciprocity has various implications for the actors involved in opposition and co-operation networks. When organisations are opposed to each other, reciprocity is almost always guaranteed. Similarly, organisations that establish political or military alliances with other organisations expect that their partners will also treat them as allies.

Other important concepts emphasise the situation of individual actors within the entire network. For instance, the overall importance, influence or prominence of an actor is often deduced from their **centrality** to the set of relations in the network. Numerous measures have been developed to measure how centrality varies according to the structural context in which actors are embedded (Borgatti, 2005[13]; Everett and Borgatti, 2010[14]). Among the most commonly used forms of centrality are degree, eigenvector, betweenness and closeness centrality:

Figure 3.2
Degree, eigenvector, betweenness and closeness centrality

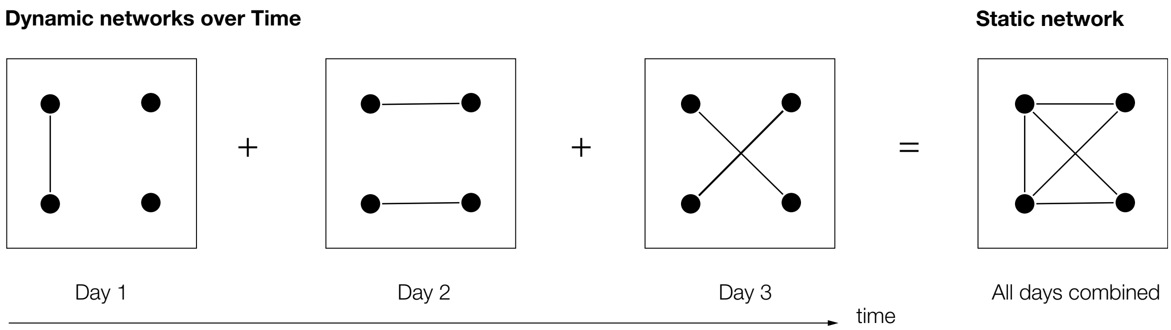


Source: OECD/SWAC (2019[15]), *Women and Trade Networks in West Africa*, West African Studies, OECD Publishing, Paris, https://doi.org/10.1787/7d67b61d-en.

- **Degree centrality**: Certain actors are central because they have numerous connections with others. Their high degree centrality indicates that they are rooted within a dense community of friends, parents or allies, which impart confidence and stability. Degree centrality is a local measure that simply counts the number of ties that an individual or an organisation possesses. It does not consider ties at further degrees of separation within the entire network, which can also have impacts on individual autonomy. In the network portrayed in Figure 3.2, for example, actors A, B and E have the highest degree centrality with five links each. Their structural positions, however, differ when the whole network is considered: while B and E are linked to other actors that are themselves well-connected, A is connected to four actors that are only linked to him or her.
- **Eigenvector centrality**: The number of relationships is often less important than their quality. If it is important to be connected to many people, it is also crucial to be connected to individuals who are themselves central, such as B and E in Figure 3.2. Eigenvector centrality measures the degree to which nodes are connected to other well-connected nodes and is an indicator of influence. Eigenvector centrality is a general measurement that reflects structural constraints within a network better than degree centrality.
- **Betweenness centrality**: Some actors are considered central because they link communities that, without them, would be disconnected. These brokers have a high betweenness centrality because they have access to resources or information that is not immediately available in their community of origin. In West Africa, large traders leverage this form of centrality by taking advantage of different legislative environments in different countries to supply markets (OECD/SWAC, 2019[15]). Actor C in Figure 3.2 has a very high betweenness centrality because it connects two subgroups.
- **Closeness centrality**: Centrality can reflect the distance that separates individuals or organisations from the rest of the network. This closeness centrality is particularly important for actors that are the closest to the highest spheres of political and economic power without actually being in charge. Closeness centrality assumes that every actor in the network is connected by at least one link, such as in Figure 3.2, where actor F is particularly far away from the centre of the network and, as a result, has quite weak closeness centrality.

The centrality of a node depends not just on the number of ties that they have established with their immediate neighbours, but also on the overall structure of the network. SNA has developed numerous metrics to capture global structural constraints and opportunities upon which individual actors have little control. While the concept of centrality can assess the structural role of an individual node, the concept of **centralisation** describes the general shape of a network, or topology. It indicates whether the network is more or less centralised according

Figure 3.3
Dynamic and static social network analysis



Source: Adapted from Uddin, S., A. Khan and M. Piraveenan (2015[18]), "A set of measures to quantify the dynamicity of longitudinal social networks", *Complexity*, Vol. 21/6, pp. 309–320.

to various centrality measures. Centralised networks are built around certain very well-connected actors who possess numerous ties to other actors (degree), are capable of playing an intermediary role between disconnected clusters (betweenness), are very close to the centre of the network (closeness) or are well-connected to other central actors (eigenvector).

An example of a very centralised network is the star network, in which all actors are connected to a central node without being connected to each other. This kind of structure is known for generating relations of dependence between the centre and the periphery while being very effective in transmitting information, orders and resources. American mafia networks are an example of a strongly centralised network in which power is concentrated in the hands of a few influential actors, who transmit orders to the bottom of the pyramid (Mastrobuoni and Patacchini, 2012[16]).

By contrast, decentralised networks have few exceptionally well-connected actors, and their measures of centralisation are generally weak. The lack of a central authority makes these networks far less capable of co-ordinating sophisticated activities than centralised networks, but also quite resilient to external attacks and more egalitarian when it comes to the distribution of roles and resources. The "leaderless" network suggested by Marc Sageman (2008[17]) to characterise the current organisation of global jihadist organisations is an example of a decentralised structure in which individual cells possess a great degree of autonomy to plan and conduct attacks around the world.

Dynamic social network analysis

Traditional SNA represents networks at single moments in time and explores the associated concepts described above with the assumption that the set of actors and relations among them are stable across the duration captured by the analysis. As this assumption is often not met with most real-world phenomena, dynamic social network analysis, or DSNA, has been advanced to explore "structural positions of actors across sets of network data that have been collected in time periods [that are] shorter than the overall duration of the longitudinal social network" (Uddin, Khan and Piraveenan, 2015: 2[18]).

Because DSNA emphasises the realisation of relationships over time, it is a fundamentally different form of investigation from a traditional SNA. Figure 3.3 illustrates some key differences between a static network approach and a DSNA approach. Given a set of actors and some relation between them, ties can be observed across a defined time interval (in this case, a total duration of three days is arbitrarily chosen, but the same approach can be applied to much longer time periods).

A traditional SNA approach would be to summarise and aggregate all the ties present at any time point during that total duration into a single network indicated by the right-most graph. This would yield one network for the time period in question but would not record information about which tie came first or second, the duration or persistence of ties over time, and so on. In other words, the resulting aggregated network gives minimal insight into the dynamic process that yielded the overall outcome. It also assumes that once a tie is present, it is permanent. In contrast, a DSNA approach would observe the same group of actors but at multiple time intervals, which allows for a consideration of the issues described above. Consequently, there is no single aggregated network associated with a DSNA. Instead, there are a series of sequenced networks, one for each observed time period.

A DSNA approach is inherently descriptive, recording when actors come and go and when ties form and end. Several key DSNA metrics have been proposed, including connectivity, communities, and influence (Nicosia et al., 2013[19]). Similar to static social network analysis, these are metrics that emphasise measurement either at the level of individual actors, such as degree centrality, or at the level of the entire network, such as network centralisation. The key difference in these DSNA metrics from their SNA counterparts is in the inclusion of time, which can influence methods that are based on tie paths, such as betweenness and closeness centrality. As tie paths may come and go over time, DSNA metrics often require some adjustment to account for this dynamism from their more traditional static counterparts (Grindrod et al., 2011[20]; Holme and Saramäki, 2012[21]).

DSNA is especially useful when a group operates over long periods, as it allows for a temporally disaggregated understanding of their relationships and actions. For example, the Islamist group Ansar al-Sharia (AaS) operated between 2012 and 2017 in eastern Libya and was responsible for more than 130 attacks during that time (ACLED, 2019[22]). Their efforts were mostly focused against the forces of the Libyan National Army (LNA), the de facto secular government in the east since 2015. As part of the larger Islamist military coalition called the Shura Council of Benghazi Revolutionaries (SCBR) formed in mid-2014, AaS routinely co-operated with other Shura Council groups, like the February 17th Martyrs and the Libya Shield Brigade. Taking a static network approach over the duration of AaS's existence would simply result in a network showing a single co-operative tie with other Shura groups. However, a finer-grain perspective over time shows that these co-operative relationships actually ebbed and flowed. AaS conducted numerous attacks with other Shura groups between June and August 2014 but operated alone for much of the remainder of 2014. Co-operation then resumed at the beginning of 2015. Without the perspective offered by DSNA, this gap in co-operation could not be observed, and shorter-term changes in a group's position in a conflict network would be invisible.

DSNA's focus on how ties may change over short time intervals has led to efforts to measure the creation and dissolution of ties, either positive or negative, among a group of actors over time (Snijders, Van de Bunt and Steglich, 2010[23]). This approach helps to understand how networks evolve, change, adapt and how they can be destabilised (Carley, Lee and Krackhardt, 2002[24]; Carley, 2003[25]; Carley and Pfeffer, 2012[26]; Everton and Cunningham, 2013[27]). The principle behind this approach is to detect changes in a network over time. In Syria, for example, examining the daily changes in overall network density among the various groups involved in the conflict showed how the United States intervention between 2014 and 2018 had two separate effects. First, anti-Assad groups increased their co-operation with each other to pursue their goals of overthrowing the regime just by taking on nominal opposition to the Islamic State. A similar effect occurred among pro-Assad groups, and Iran activated and mobilised several militias that all co-operated with one another. The net effect was a steady increase in the overall amount of co-operation among many groups, even as conflict remained focused on the Syrian regime and the Islamic State rather than with each other. The second effect was to draw in other foreign interveners, primarily the Russians, in fear of a defeat for Assad. This served to prop up Assad in a way the Iranians could not, and made it harder for any group to change their position. Until either the Islamic State or Assad was defeated, the patterns of both co-operation and opposition were going to be difficult to disrupt (Radil and Russell, 2019[28]).

NETWORKS AND CONFLICT

SNA and DSNA are particularly well adapted to capture the complexity of contemporary conflicts due to their ability to represent and model networks of large numbers of actors that contain both positive and negative relations. In network science, these configurations of actors are known as signed networks (Harrigan, Labianca and Agneessens, 2020[29]). Positive ties develop when social actors overcome collective-action problems, co-operate based on trust or a shared ideology, co-ordinate activities at a distance, distribute resources, disseminate ideas and make joint decisions. Alliances between states or rebel groups are typical of positive-tie networks. By contrast, negative ties develop among actors that dislike, avoid or fight one another, as when one terrorist group launches an attack against civilians or government targets.

There are important differences between networks with positive and negative ties (Everett and Borgatti, 2014[30]). Networks based on friendship, alliance and collaboration typically possess more ties and display more clustering of ties around actors that share similar values than networks containing negative ties, because actors tend to have more friends than enemies (Huitsing et al., 2012[31]). For obvious reasons, networks with positive ties also tend to allow the sharing of more resources, ideas and knowledge than do networks based on hatred and avoidance, which tend to aim at neutralising foes. As a consequence, many centrality measures are based on the assumption that social networks serve as conduits for flows of information, advice or influence. These assumptions are unrealistic in the case of negative tie networks where very little actually circulates, except violence itself, of course. For example, being connected to numerous actors is an asset in a co-operative network where having several friends is synonymous with social prestige or influence. In a network of rivals, however, having many enemies is a liability that can threaten the existence or the daily operations of an organisation.

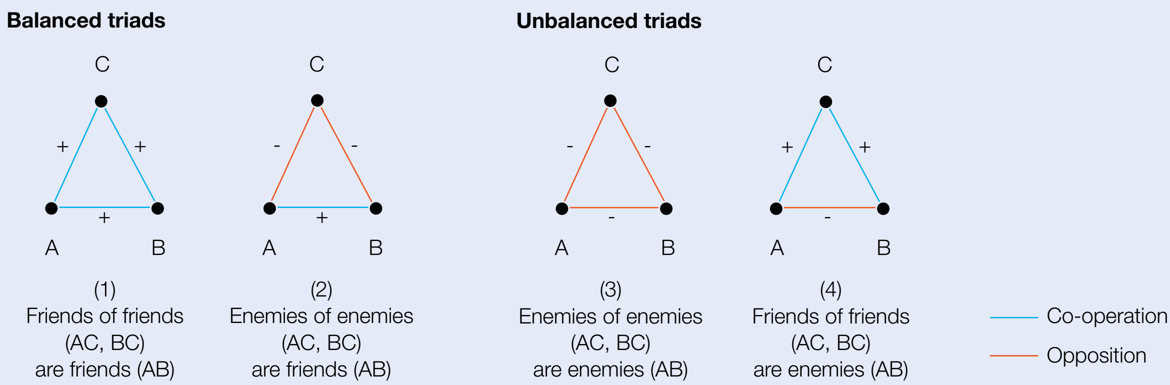
A growing literature in network science and related social sciences suggests that, despite their differences, co-operative and conflictual networks should be analysed simultaneously (Labianca and Brass, 2006[32]; Grosser, Kidwell-Lopez and Labianca, 2010[33]; Rambaran et al., 2015[34]; Yap and Harrigan, 2015[35]; Marineau, Labianca and Kane, 2016[36]). This is because most if not all individuals or organisations are embedded in both types of relations and make choices by drawing on their understanding of their options relative to their allies and enemies. This is an especially relevant point to consider in conflict networks. With that in mind, there are several key concepts in SNA that have been applied to signed networks and are useful in explaining the interplay between the two types of relations in this study. These include the concepts of structural balance, transitivity, spectral embedding and centrality. Each is discussed in turn below.

Balance within groups of actors

Perhaps the most straightforward way to incorporate alliances and rivalries in a conflict network is to use structural balance theory, which assumes that social relations among a group of three actors (known as a triad) can either be stable or unstable, depending on the number of positive and negative ties they have. Balance theory argues that relations among a triad of actors are stable over time if they have either no negative ties or if two out of the three possible ties are negative (Doreian and Krackhardt, 2001[37]; Hummon and Doreian, 2003[38]). A triad formed by three actors, for example, is theoretically stable if all the possible relations are positive or if two actors have negative relations with a third party (Figure 3.4). The first case represents the idea that "friends of a friend are friends" while the second case represents the idea that "enemies of an enemy are friends". In contrast, triads formed of two positive and one negative tie ("friends of a friend are enemies") and of three negative ties ("enemies of an enemy are enemies") are theoretically unstable.

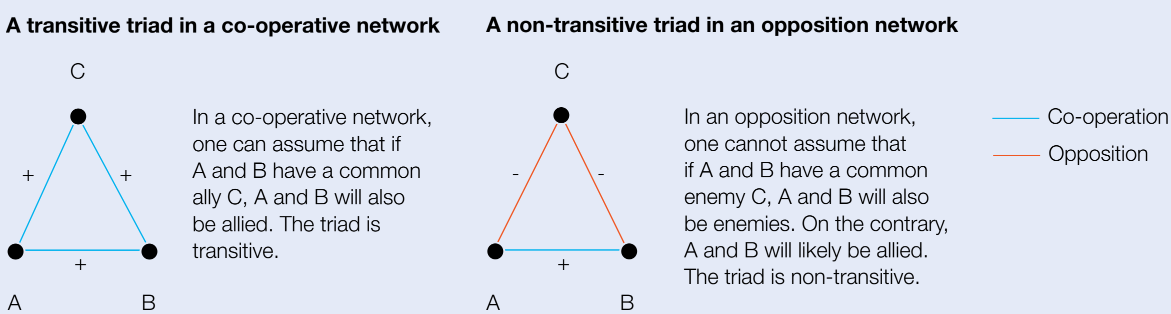
Over time, balance theory argues that such unbalanced triads will evolve over time towards a balanced triad. This is because the unbalanced

Figure 3.4
Balance theory



Source: Authors.

Figure 3.5
Transitivity



Source: Authors.

triads involve pressures on each actor that can only be resolved by altering views, behaviours and relationships. For example, consider triad 4 in Figure 3.4 where two actors A and B, who share a common ally (actor C), but are in conflict with each other. Actor C will find it difficult to preserve his/her positive relationship with both A and B while these actors are opposing each other. Over time, actor C may find him or herself pressured to "pick a side", which would alter the relationship, causing it to become balanced, as in triad 2. This principle is commonly demonstrated in international relations (Doreian and Mrvar, 2015[39]). States that have shared a common enemy are less likely to fight each other and are more likely to become allies than a randomly chosen sample of countries that interacted within the international system (Lerner, 2016[40]).

Transitivity within groups of actors

The issues of structural balance described above draw on another concept in SNA called transitivity, a principle that assumes that two actors sharing a connection to a third actor are likely to be connected to each other as well. Co-operative networks are usually transitive, meaning that if actors A and B have a common friend C, A and B will likely be friends. Networks containing negative ties are well known for having a low level of transitivity (Everett and Borgatti, 2014[30]), and in rivalry networks, it is unrealistic to assume that if A and B are fighting C, A and B are also enemies (Figure 3.5). Quite the contrary: it is more likely to assume that A and B are allied against C, and therefore the triad between A, B and C is non-transitive.

Box 3.2

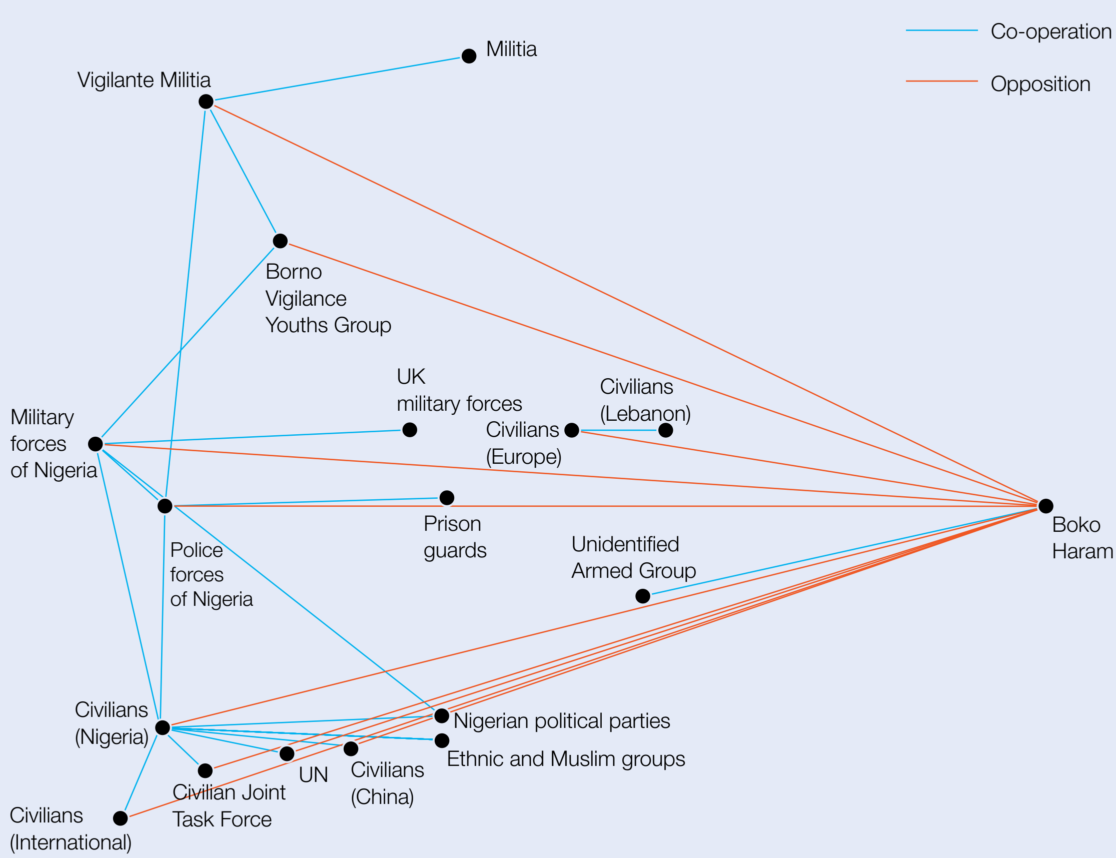
Visualising signed networks

Sociograms of a signed network can be quite visually complex. As a consequence, visualisation methods have been developed specifically for them. A meaningful way to visually represent a network with both positive and negative ties is to use the distance between any pair of actors as a proxy for their relational dissimilarity. Known as spectral embedding, this technique makes it possible to place the nodes that represent organisations at the position that best balances the "pull" of allies against the "push" of enemies (Zheng, Skillicorn and Walther, 2015[42]). In this type of sociogram, rival actors appear visually far from each other, while allies are placed close to one another.

Spectral embedding shows that groups with similar allies and foes form clusters that correspond to their structural position in North and West Africa (Walther, Leuprecht and Skillicorn, 2020[43]). The contrast between allies and enemies is particularly evident for Boko Haram, who is opposed to virtually every other actor in the region, particularly governmental forces and civilians from Nigeria and Cameroon (Figure 3.6).

Figure 3.6

Spectral embedding showing Boko Haram and its enemies



Source: Adapted from Walther, O., C. Leuprecht and D. Skillicorn (2020[43]), "Political fragmentation and alliances among armed non-state actors in North and Western Africa (1997–2014)", *Terrorism and Political Violence*, Vol. 32/1, pp. 167–186.

(Continues overleaf)

(Box 3.2 continued)

Spectral embedding also shows that groups with similar allies and enemies have similar patterns of aggression. The attack patterns of Ansar Dine, the Movement for Unity and Jihad in West Africa (MUJAO) and al-Mourabitoun, three jihadist groups from Mali, differ from those of the Armed Islamic Group (GIA), the Salafist Group for Preaching and Combat (GSPC) and AQIM, who originally came from Algeria. These findings suggest that the propensity to use political violence corresponds to an organisation's position in the network rather than to their actions per se. In other words, mapping how violent actors are connected enables understanding how violent they can be.

Source: Original text provided by Olivier Walther.

In North and West Africa, low levels of transitivity (1%) have been found in the conflict network connecting violent organisations in the region since the late 1990s (Walther, Leuprecht and Skillicorn, 2018[8]) (Box 3.2 and Figure 3.6 for a visualisation of Boko Haram and its enemies). This suggests that enemies of enemies are indeed allies. In Syria, where infighting between groups with a common opponent is frequent, a substantial level of transitivity of 15% has been observed in recent years (Kuznar, Jonas and Astorino-Courtois, 2018[41]).

Centrality

An emerging approach to examining signed networks is to jointly measure the importance or centrality of each actor relative to both types of relationships. However, most traditional metrics have examined centrality for positive ties separately from negative ties, as signed networks assume differing conceptualisations of power in a network. Smith et al. (2014[44]) characterised these approaches as "power-as-access" to resources and "power-as-control" over resources. Positive networks tend to be associated with the power-as-access perspective, while negative or mixed networks tend to be associated with power-as-control. For example, access to other actors in a network, either directly (as with degree centrality) or indirectly (eigenvector centrality), can be seen as a proxy for power if flows such as information exchange are unimpeded in a network of allies. In a network of rivals, such flows are often curtailed or manipulated to the detriment of other actors. In such circumstances, it would be important to be less reliant on connections that may be interrupted or restricted. In short, an actor is assumed to benefit from many ties in a positive network but the same condition in a negative network would be a detriment.

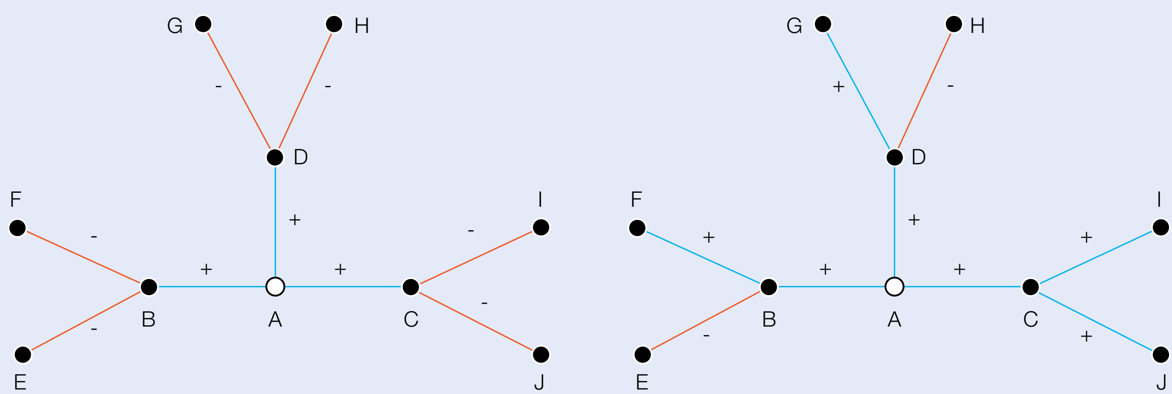
For this reason, traditional centrality metrics have either been implemented only for positive networks or calculated separately to account for the differences between positive and negative tie patterns (e.g. Bonacich power centrality; Bonacich, 1987[45]). However, new metrics have been recently proposed that strive to produce a joint account of centrality for signed networks. This is the logic behind the development of the Political Independence Index or PII (Smith et al., 2014[44]), which builds on the power-as-control approach when there are both positive and negative ties. The PII is a centrality measure that assumes that powerful actors are those with few direct adversaries and with many allies that rely primarily on them or who have few other alternatives for support. Conversely, weak actors are those with many direct adversaries and few allies that largely rely on them.

This principle is illustrated in Figure 3.7, which compares the structural autonomy of an actor connected to several allies in two different situations. On the left-hand side of the figure, A has three allies B, C and D, who themselves have many enemies (E-J). This makes B, C and D dependent on A for their security and therefore increases the structural autonomy of A. On the right-hand side of the figure, A has the same number of allies, but each of them has many allies. This makes B, C and D autonomous from

Figure 3.7

Political independence

A network of allies providing greater autonomy to A | **A network of allies reducing the autonomy of A**



A has three allies B, C and D who themselves have many enemies (E-J). This provides greater structural autonomy to A, who can choose from several allies who themselves have little choice but to ally with A.

A has three allies B, C and D who themselves have many allies (F, G, I, J). This reduces the autonomy of A because B, C and D are not constrained to ally exclusively with A.

Co-operation — Opposition

Source: Adapted from Smith, J. et al. (2014[44]), "Power in politically charged networks", *Social Networks*, Vol. 36, pp. 162–176

A for their security and therefore decreases the structural independence of A.

Because the presence of positive ties among other actors is considered a detriment for the PII measure, it may have limited utility for conflict networks characterised by numerous alliances. For this reason, the report utilises another important new joint metric called the Positive-Negative or PN centrality measure (Everett and Borgatti, 2014[30]). PN centrality draws on both notions of power and reflects the idea that having positive ties is not necessarily a detriment to an actor. Although PN centrality has not yet been widely applied in the literature, it has significant promise as a centrality measure as it attempts to balance both approaches of power in a signed network. This report is the first application of PN centrality to the study of conflict. It will use PN centrality to identify which actors are the most prominent or important in the region when taking both their alliance and rivalries into consideration.

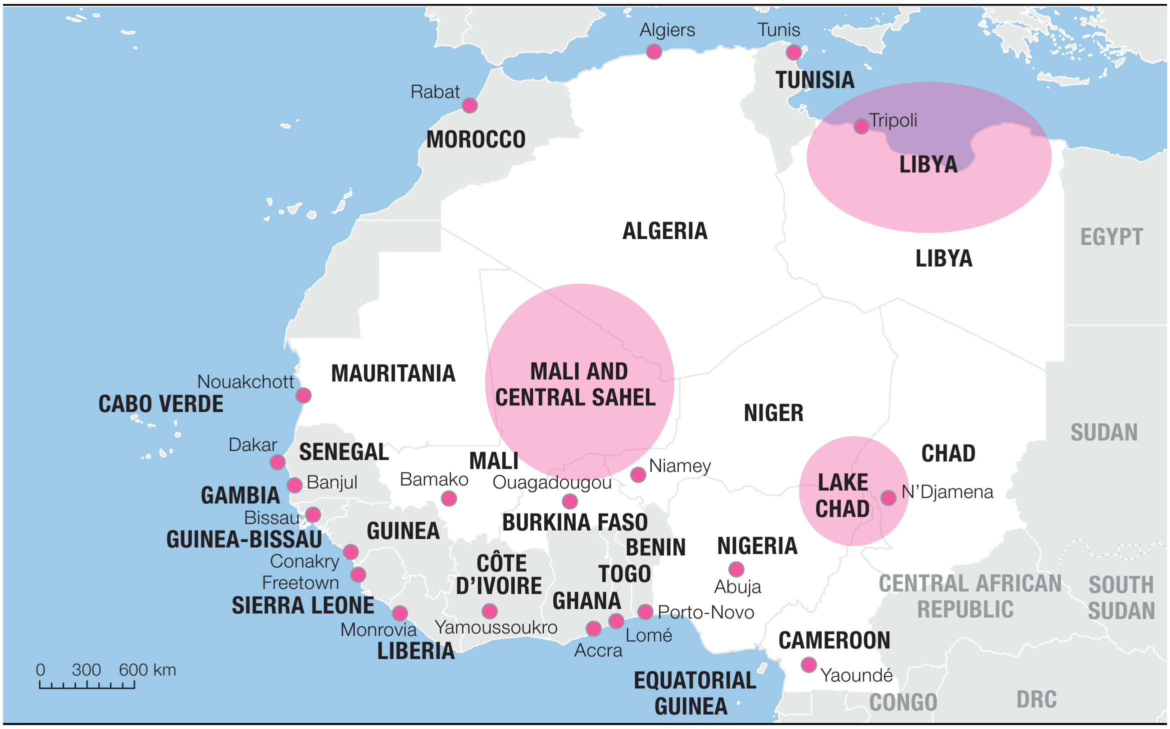
HOW TO ASSESS CONFLICT NETWORKS IN NORTH AND WEST AFRICA

A regional approach and disaggregated data

This report leverages political event data from the Armed Conflict Location & Event Data Project (ACLED), which provides detailed and georeferenced information on violent events and actors in conflict since 1997 (Raleigh et al., 2010[46]; ACLED, 2020[47]). The analysis is conducted across 21 North and West African countries, including Algeria, Benin, Burkina Faso, Cameroon, Chad, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Libya, Mali, Mauritania, Morocco, Niger, Nigeria, Senegal, Sierra Leone, Togo and Tunisia. (Map 3.1). This rather large geographical scope reflects both the origins and

Map 3.1

Location of case studies



Note: The pink circles indicate the case studies discussed in this report.

Source: Authors.

current mobility patterns of violent organisations, which can hardly be contained within a single country or region.

This regional analysis is followed by a study of three case studies: the Mali insurgency and its consequences in the Central Sahel since 2012; the Boko Haram insurgency in the Lake Chad region since 2009; and the First and Second Libyan wars since 2011. In these regions, violent organisations have developed rapidly since the mid-2000s and have extended beyond state boundaries, causing significant numbers of violent events and deaths. In each of the regions, regional or international coalitions have intervened militarily to protect civilians and stop the territorial expansion of jihadist organisations. How these interventions have contributed to reshuffling the co-operative and opposing relationships of local actors in conflict remains largely unknown.

From 1 January 1997 to 30 June 2020, the ACLED dataset provides detailed information on 36 760 events that have caused 155 375 fatalities in North and West Africa. ACLED distinguishes between violent events, demonstrations and non-violent actions, 6 types of events and 25 sub-event types. The study focusses on three types of politically motivated violent events exclusively: battles, explosions and remote violence, and violence against civilians (Table 3.2). Non-violent events such as agreements, arrests, disrupted weapons use, headquarters established, looting, demonstrations and non-violent transfer of territory are excluded from the analysis.

- A **battle** is defined by ACLED (2019, p. 7[22]) as "a violent interaction between two politically organised armed groups at a particular time and location." Battles can occur between any state and non-state actors and involve at least two armed and organised actors. This category is subdivided into three sub-event types, depending on whether non-state actors or government forces overtake territory or whether there is no territorial change.
- **Explosions** and **remote violence** are "one-sided violent events in which the tool for engaging in conflict creates asymmetry by taking away the ability of the target to respond" (ACLED, 2019, p. 9[22]). These acts

Table 3.2

Number of violent events and fatalities in North and West Africa, by type, 1997–2020

Type	Number of violent events	Number of fatalities
Battles	**16 309**	**77 637**
Armed clash	14 508	68 521
Government regains territory	966	4 815
Non-state actor overtakes territory	835	4 301
Remote violence	**6 368**	**22 429**
Air/drone strike	2 138	7 931
Grenade	56	50
Remote explosive/landmine/improvised explosive device (IED)	2 341	7 935
Shelling/artillery/missile attack	1 334	1 576
Suicide bomb	499	4 937
Violence against civilians	**14 083**	**55 309**
Abduction/forced disappearance	1 869	0
Attack	12 067	54 393
Sexual violence	147	916
Total	**36 760**	**155 375**

Note: Data available through June 2020.

Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

of violence can be carried out using devices such as bombs, grenades, improvised explosive devices (IEDs), artillery fire or shelling, missile attacks, heavy machine-gun fire, air or drone strikes or chemical weapons.

- **Violence against civilians** is a growing concern in the region. They include "violent events where an organised armed group deliberately inflicts violence upon unarmed non-combatants. By definition, civilians are unarmed and cannot engage in political violence. The perpetrators of such acts include state forces and their affiliates, rebels, militias, and external/other forces" (ACLED, 2019, p. 11[22]). Civilians are not just caught up in the crossfire that inevitably occurs between state forces, rebels and violent extremist organisations. They have also become the primary objectives of many insurgencies for whom controlling the resources, allegiances, social behaviours and religious beliefs of civilians are often more important than holding territory (OECD/SWAC, 2020[48]). In consequence, the cost paid by civilians to modern conflicts has increased dramatically, particularly in West Africa where the number of civilian deaths reached 5 029 victims in 2019. The number of direct attacks, kidnappings and sexual assaults against civilians now exceeds the number of armed battles between state forces and armed groups in West Africa (Figure 3.8).

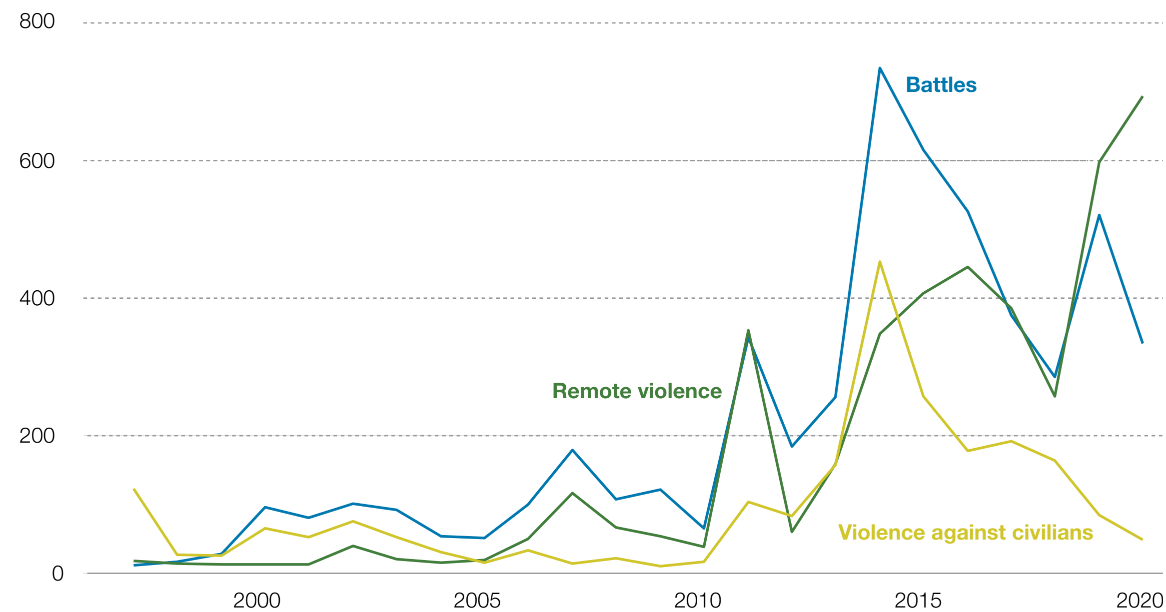
A focus on organisations

The study builds on the classification provided by ACLED, which distinguishes between eight categories of actors based on their goals and structure and, where possible, on their "spatial dimension and relationships to communities" (ACLED, 2019, p. 19[22]) (Table 3.3). Some of these actors are formal organisations, such as state forces, rebels, militias and external forces. Other actors are informal groups of people (ethnic communities, rioters, protesters) or non-combatant categories (civilians).

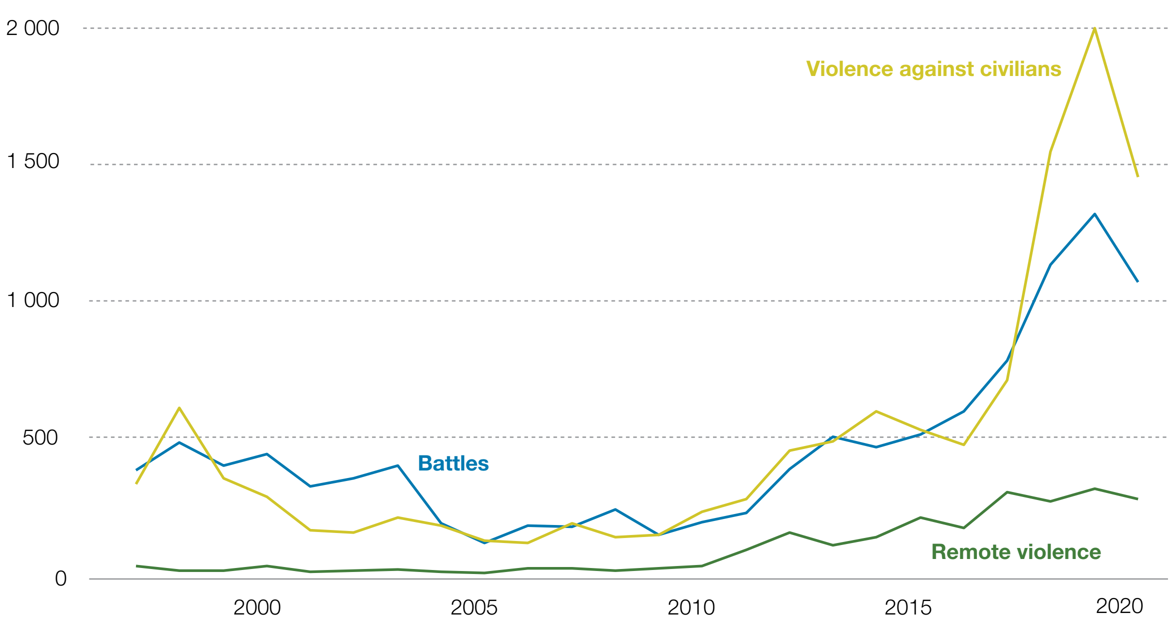
- **State forces** are collective actors that exercise de facto state sovereignty over a

Figure 3.8
Violent events in North and West Africa by type, 1997–2020

North Africa



West Africa



Note: Data available through June 2020.

Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

Table 3.3

Number of actors in North and West Africa by category, 1997–2020

Type of actors	Number	Examples
State forces	378	Military forces of Algeria, Police forces of Mali
Rebels	131	Polisario Front, National Movement for the Liberation of Azawad (MNLA), Al Qaeda in the Islamic Maghreb (AQIM)
Political militias	459	Democratic Alliance of 23rd May for Change (ADC), Ansar Sharia, Al-Salafiya Al Jihadia
Identity militias	1 405	Chaamba Ethnic Militia, Raffour Communal Militia, Group for Supporting Islam and Muslims (JNIM)
Rioters	3	Rioters (Chad)
Protesters	6	Protesters (Togo)
Civilians	696	Civilians (Mali)
External forces	68	Military forces of France, NATO
Others and unknown	12	Nigeria Petroleum Development Company (NPDC)
Total	**3 158**	

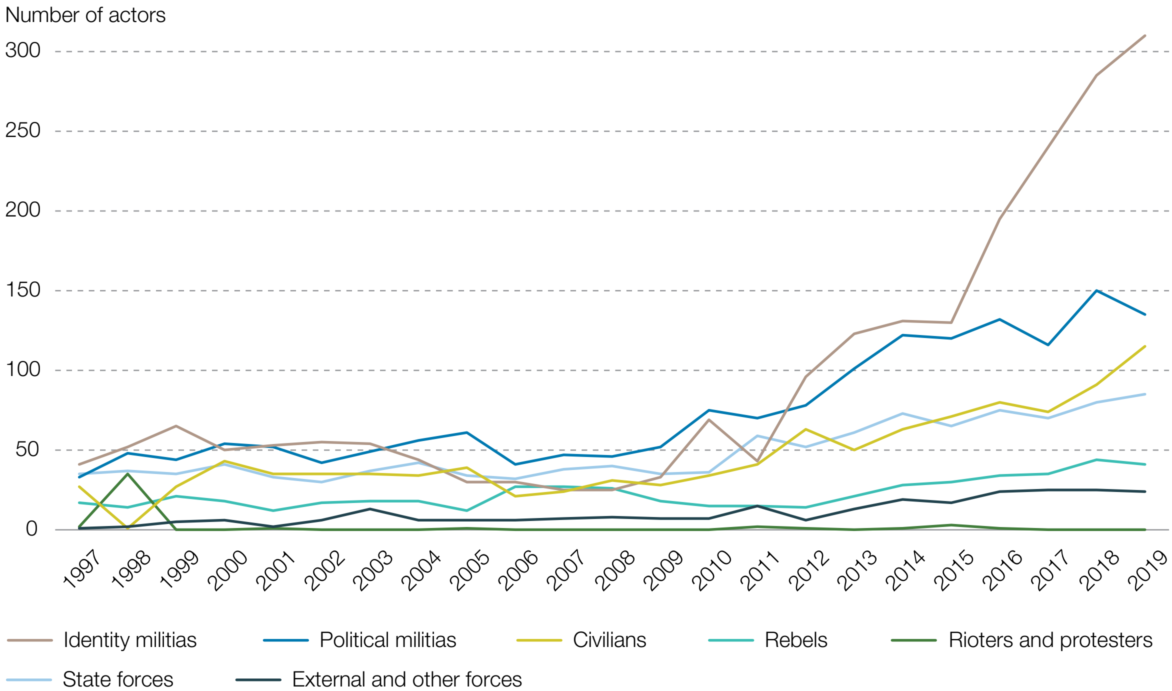
Note: Data available through June 2020.

Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

given territory. They include military and police forces from the region. External military actors such as the French armed forces, for examples, are coded separately. In Libya, competing groups that have a claim to government functions, such as the National Salvation Government, are coded as state forces. State forces from the region represent 13% of the actors.

- **Rebel groups** are organisations whose political agenda is to overthrow or secede from a given state. They represent less than 5% of the recorded actors. Splinter groups or factions that emerge from a rebel group are recorded as distinct actors.
- **Militias** are by far the most represented category of actors, with 1 864 unique organisations overall, which represents almost 60% of all violent actors identified by ACLED in the region. The numerical importance of militias in North and West Africa reflects a larger trend on the continent, where political elites, religious leaders, and community strongmen use political and identity militias as "private armies" to compete over access to resources, settle disputes and strengthen local power (Raleigh, 2016[49]). Since the 1990s, competition within and between political parties has increased the use of these informal violent groups in democratising states (Figure 3.9).
- ACLED defines **political militias** as organisations whose goal is to influence and impact governance, security and policy in a given state through violent means. Unlike rebel groups, political militias "are not seeking the removal of a national power, but are typically supported, armed by, or allied with a political elite and act towards a goal defined by these elites or larger political movements" (ACLED, 2019, p. 22[22]). **Identity militias** are a heterogeneous group of militants structured around ethnicity, religion, region, community and livelihood. Events perpetrated by identity militias are often described as "communal violence" as they involve groups embedded in local conflicts over resources and power. This category includes tribal, communal, ethnic, local, clan, and religious and caste militias (ACLED, 2019[22]).
- ACLED identifies several categories of **civilian actors**. Firstly, **rioters** are individuals or groups engaged in disorganised violence during demonstrations. They are unarmed yet may engage in violent

Figure 3.9
Evolution of actors in North and West Africa by category, 1997–2019



Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

activities against civilians, government forces or other armed groups. Rioters are identified by their country of origin. Those affiliated with a political party or leading an event are named in the respective associated actor category. Secondly, **protesters** are peaceful and unarmed demonstrators who engage in a public event. They are identified by their country of origin. Those affiliated with a political party or leading an event are named in the respective associated actor category. Finally, **civilians** refer to the unarmed and unorganised victims of violent events. They are identified by their country of origin and represent 23% of the actors.

- **External and other forces** include international organisations, foreign military forces, private security firms and independent mercenaries engaged in violent events. Military forces operating outside of their home state are also included in this category, as when Cameroonian, Chadian and Nigerien forces fight Boko Haram in neighbouring Nigeria, for example.

This report follows ACLED's classification of actors and uses the "organisation" as its main unit of analysis for all combatant actors. **Organisations** are defined as political actors with a particular purpose and a distinct structure, such as AQIM, a formal organisation with a leader, an executive and religious council, and several committees responsible for military affairs, finance, medical care, politics and international relations (Counter-Extremism Project, 2019[49]). Organisations are an intermediary unit of analysis that lie below political movements, which are defined as collective efforts by people working toward a common objective, but above groups and individuals (Table 3.4). In northern Mali, for example, the rebellion comprises a coalition of several nationalist organisations (Coordination of Azawad Movements, or CMA) and a pro-government coalition of militias and other "popular" fronts (known as Plateforme). Each of these movements contains numerous organisations such as the National Movement for the Liberation of Azawad (MNLA) and the High Council for the Unity of Azawad (HCUA) that

Table 3.4
Levels of analysis

Level	Definition	Example in Mali
Movements	Movements are a collective effort by people working toward a common objective.	The jihadist movement
Organisations	Organisations are discrete institutions or associations that have a particular political purpose; they are made up of members and have administrative and functional structures.	Katibat Macina, a jihadist organisation founded in 2015 that joined JNIM in 2017
Groups	Subgroups are collective subcomponents of organisations; they usually perform different functions under the direction of the overall organisation.	The Katibat Serma, a semi-autonomous group of Katibat Macina operating between Gao and Mopti
Individuals	Individuals are single human beings.	Abu Jalil al Fulani, the leader of Katibat Serma

Source: Adapted from OECD/SWAC (2020[48]), *The Geography of Conflict in North and West Africa*, West African Studies, OECD Publishing, Paris, https://doi.org/10.1787/02181039-en.

maintain separate structures and only join the movement for advancing their individual goals.

The boundaries between movements, organisations, groups and individuals are often thin in North and West Africa, where mergers and splits among armed actors are particularly frequent. In Mali, for example, the MNLA calls itself a movement because it results from the fusion of several rebel groups. However, it is also an organisation with its own hierarchy, political and military wings, public relations, social media office and flag (Lecocq and Klute, 2019[51]). Similarly, the Group for Supporting Islam and Muslims (JNIM) resulting from the merger in 2017 of Ansar Dine, Katibat Macina, Al-Mourabitoun and the Saharan branch of AQIM can be seen as a new organisation or as a coalition of jihadist organisations that maintain great strategic and operational autonomy.

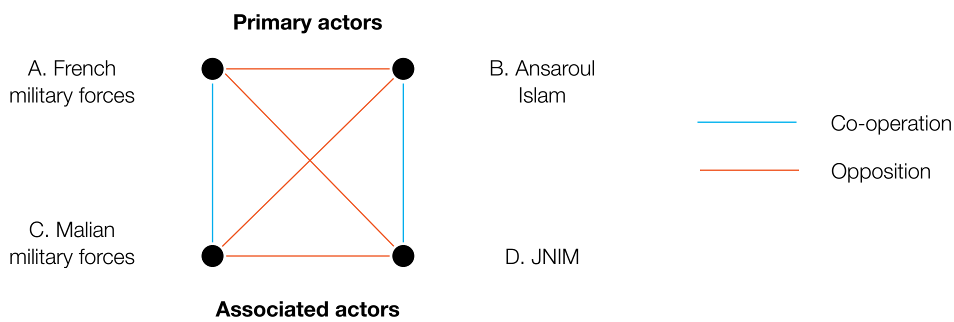
Given this framework, it is important to clearly distinguish between the types of actors that appear in this study that fit the conceptualisation of an "organisation", such as AQIM, and those that appear, but are clearly not an organisation, such as "civilians". As a general social category, civilians do not align with any of the four levels presented in Table 3.4 and cannot be meaningfully said to possess any sense of political agency. This means there is not a conscious and collective pursuit of a goal for this type of actor as there are with the other levels. For this reason, civilians are present in the study but are not treated the same as an organisation. In particular, the study presumes that civilians can only be the targets of violence but that these actors cannot engage in partnerships with actual organisations. Consequently, a dyad involving a civilian actor and an organisation can only result in a negative tie between them if civilians are targeted for violence by the organisation. As it is not possible by definition for a civilian actor to be involved in an active alliance or co-operative relationship, this type of dyad cannot result in a positive tie.

A focus on politically violent events

The main purpose of the ACLED database is to record politically violent "events". An **event** is defined as "a single altercation where often force is used by one or more groups toward a political end" (ACLED, 2019, p. 6[22]). Because a given event can involve many different types of actors that can have friendly or conflictual relationships, this study makes four primary adjustments to the ACLED dataset when it is used to model networks.

The first change is to create a unique name for each organisation. In the ACLED database, some government forces are sometimes identified differently depending on their patterns of behaviour or time period. For example, the actor called the "Military Forces of Mali" in ACLED is listed six different ways in the database, according to the regime they have served and the type of unit involved in the events. The study simplifies this classification

Figure 3.10
Primary actors and associated actors



Source: Authors.

and considers the military of each country as the same actor without other qualifiers. The same logic is applied to police forces and other governmental agencies.

The second change involves the fact that ACLED data do not classify organisations according to their ideology. As a result, organisations that share an Islamist agenda are usually coded either as rebels (AQIM, Ansar Dine, Boko Haram, Islamic State, MUJAO), political militias (Ansar Sharia, Those Who Signed in Blood, Libyan brigades) or identity militias (JNIM). Because much of today's political violence in North and West Africa is due to organisations with a religious agenda, the study creates a sub-category of actors coded "Violent Islamist Organisations". The organisations listed in this sub-category: 1) promote a "vision of Islamic political order that rejects the legitimacy of the modern sovereign nation-state and seeks to establish a pan-Islamic polity or renewed caliphate"; and 2) emphasise "violent struggle (jihad) as the primary or even the exclusively legitimate method for the pursuit of political change" (Mandaville, 2014, p. 330[52]). The database contains 153 such organisations involved in political violence in the region from 1 January 1997 to 30 June 2020.

The third change addresses how the ACLED dataset records multiple actors involved in a single event. ACLED describes (up to) four actors in each event: a primary actor involved in a violent incident (actor A), a collaborator with actor A in the attack (actor C), a second primary actor involved in the incident (actor B), and a secondary collaborator with actor B (actor D). Actors C and D are coded as "associated" actors in the ACLED database, which means that they "may be allies in actions, like two armed organised groups that are engaging in attacks against a common enemy" (ACLED, 2019, p. 18[22]). For example, on 29 March 2019, the French (A) and Malian (C) military forces conducted a joint operation targeting presumed Ansaroul Islam (B) and JNIM (D) militants in the Douentza region in Mali, killing an estimated ten people (incident MLI2755). The two primary actors were the French military (A) and Ansaroul Islam (B), and the associated actors were the Malian military (C) and JNIM (D). Taken together, these fours actors that were involved in the event form a network that can be decomposed into four different pairs of actors (known as dyads), and three groups of three actors (triads) (Figure 3.10).

In less than 2% of the incidents listed between January 1997 and June 2020, ACLED codes two or more actors in the same associated actor field, as when the explosion of an IED causes the death of both civilians and military forces. In these cases, rather than just four actors (two primary actors and two associated actors), there can be several additional associated actors. This causes a problem when the data is transformed into a network, in which a node in the network can only represent a single actor. In order to address this issue, the study duplicates the events in which more than two primary actors are involved as an ally or an enemy and divides the total number of fatalities of each event by the number of newly created events.

Table 3.5
A double-entry table representing oppositional events between four actors

	Ansar Dine	MUJAO	French forces	Malian troops
Ansar Dine	-	0	72	61
MUJAO	0	-	17	19
French forces	72	17	-	0
Malian troops	61	19	0	-

Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

Table 3.6
A double-entry table representing co-operation events between four actors

	Ansar Dine	MUJAO	French forces	Malian troops
Ansar Dine	-	11	0	0
MUJAO	11	-	0	0
French forces	0	0	-	52
Malian troops	0	0	52	-

Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

Finally, as this study does not consider civilians to have political agency, all instances of co-operative ties involving civilians have been removed. In general, these outcomes would have only been the result of ACLED recording that two groups of civilians, or of civilians and an organisation, were both attacked in the same event. While this was not common, including such outcomes as examples of co-operation would add little to the understanding of the behaviour or conduct of organisations in the region.

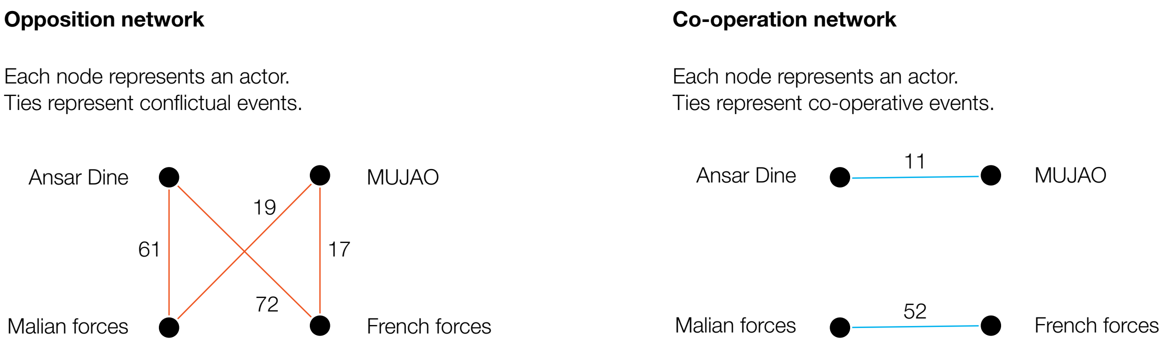
Building opposition and co-operation networks

The first step of the network analysis is to build two square matrices, which contain the names of all the organisations and other types of actors involved in at least one violent event from 1997 to 2019. In SNA, this is called an **adjacency matrix**, and it contains as many rows and columns as there are actors in the dataset. Each matrix can be represented as a double-entry table. The cells of the matrix are used to record information about the interactions or relationships between each pair of actors.

The cells in the first matrix (Table 3.5) record the number of events that have resulted from the confrontation of actors. Armed groups are often weak and try to avoid battles in the region. Therefore, the number of fatalities can be a misleading indicator of the intensity of conflict. This table then uses events instead of fatalities to provide the basis for an **opposition network**, which can provide crucial information on the intensity of political violence across the region. For example, between 2012 and 2019, jihadist organisations such as Ansar Dine and MUJAO have regularly confronted Malian and French military forces (Table 3.5). In this case, actors did not attack themselves and, therefore, the diagonal of the matrix is empty. However, violent events can result from friendly fire between actors on the same "side".

The cells in the second matrix (Table 3.6) also represent events but only counts those events in which two actors are associated with each other in a co-operative sense. Therefore, each cell is coded according to the number of times that actors have collaborated with each other against a common enemy. This **co-operation network** provides information on the coalitions that form

Figure 3.11
Opposition and co-operation networks



Source: Authors.

between actors and is an indispensable complement to the opposition network presented above. The example provided in Table 3.6 shows quite clearly that co-operation essentially takes place between jihadist organisations and between government forces.

The next step of the network analysis is to transform these matrices into a social network where the actors represent the organisations and the ties their alliances or rivalries (Figure 3.11). The social network of opposition shows negatively weighted ties between rivals. The social network that represents co-operation contains positively weighted ties between allies. Unfortunately, the ACLED data is coded in such a way that it is not always possible to distinguish between the perpetrator and the victim of an attack. The only exception is when the victim is a civilian, in which case the attacker is coded as Actor 1 and the civilian victims as Actor 2. Because ACLED does not provide information on the responsibility of the attacks, the ties have no direction associated with them, and the network is undirected. As a result, the matrix that represents clashes between actors is symmetric: there are as many events resulting from the confrontation between Ansar Dine and French forces than from French forces and Ansar Dine, for example.

Modelling dynamic networks

The final step is to model changes in both types of networks over time. To do so requires turning the list of events provided by ACLED into a list of paired actors. ACLED records all the actors that were involved in an event together, but social network analysis depends on listing actors' relationships with each other pairwise, as a dyad. To turn event data into dyadic event data, the study transforms each event into a series of dyads formed by of all the pairs of actors that were involved in the event. For example, if actors A and B are involved in a skirmish against C, this event will be listed three times to show all three pairings of actors involved: A and B co-operate, A fights C, and B fights C. This process is illustrated in Table 3.7 and Table 3.8, which show how a series of events involving two actors was progressively transformed into a series of relationships between pairs of actors.

This example uses the complicated relationship between a local coalition of Islamist militias known as the Shura Council of Mujahideen in Darnah, in eastern Libya, and the Libyan National Army (LNA), led by Field Marshal Khalifa Haftar. Following ACLED (2020[47]), the latter group is referred to as the Haftar Faction. The Haftar Faction is the military of the Tobruk-based House of Representatives (HoR), the mostly secularist governing body elected in Libya's contested election of 2014. It has battled the Tripoli-based Government of National Accord (GNA) for control of Libya since 2014 (Lacher, 2020[53]). Due to this legacy, the Haftar faction is generally secularist and opposed to Islamists, including Darnah's Shura Council. This ideological rift led to an intense rivalry in Darnah: from late 2014 to late 2018, the two groups fought

Table 3.7
Events involving Libya's Haftar Faction and the Shura Council of Mujahideen in Darnah

Event date	Actor 1	Associate actor 1	Actor 2	Associate actor 2
1 September 2015	Haftar Faction		Shura Council	
25 September 2015	Haftar Faction		Shura Council	
11 February 2016	Haftar Faction		Shura Council	
22 February 2016	Islamic State		Shura Council	Haftar Faction
20 April 2016	Haftar Faction	Shura Council	Islamic State	
21 April 2016	Haftar Faction		Shura Council	

Note: The first event is fictional and is present only to illustrate how temporally close events are consolidated into one tie.
Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

on 164 occasions and co-operated on just two occasions (ACLED, 2020[47]).

The example below examines the period containing the two instances of co-operation, when the groups temporarily abandoned their rivalry to face their common enemy, the Islamic State. Once the Islamic State had retreated from Darnah, the Shura Council and the Haftar Faction began fighting each other once again.

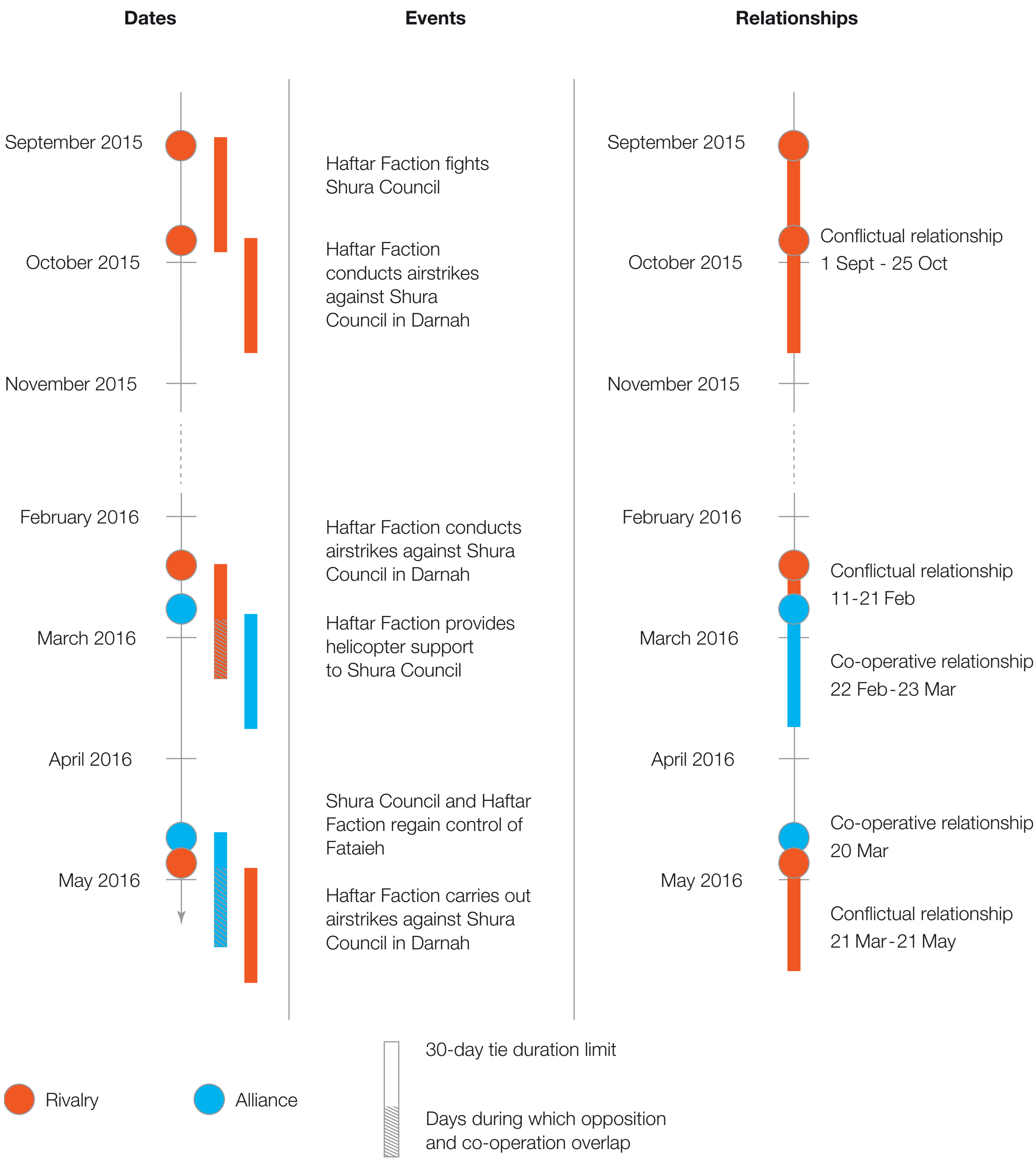
Once the event data is transformed into the pairs of actors involved, the study also records whether the relationship between that pair of actors in the event is oppositional or co-operative. These pairs of actors are then treated as a cumulative list of relationships (or an **edgelist** in SNA) that can be used to produce an adjacency matrix for any given time period or interval. The base time interval for the dynamic network analysis in the study is a single day. This means that the opposition and co-operation networks are each divided into one-day intervals during which network data is collected on the sets of enemies and of friends for each belligerent.

In addition to the steps described above, this study also uses the ACLED event data of interactions between two actors to define the duration of the actors' relationships over time. The study draws from the literature on temporal networks to assume that while an event will mark the initiation of relationship (either oppositional or co-operative) between two actors, the relationship itself will not continue indefinitely over time (Falzon et al., 2018[54]). Instead, the report establishes a base relationship duration of 30 days from an event. Once 30 days has passed since the initiation of a relationship, the relationship ends if no other events occur. This 30-day duration was empirically established by calculating the median duration between events among a pair of actors in the ACLED dataset.

This study also addressed how relationships may overlap temporally with two interrelated assumptions. First, when considering the same type of relations (either positive or negative but not a mix of both), the 30-day duration proceeds from the most recent event. In this way, events that occur in less than 30 days of each other can combine to form a continuous duration longer than 30 days for the relationship. Second, when considering the two different types of relationships (a mix of positive and negative), the 30-day duration for one relationship is always interrupted by an event to establish the beginning of an alternative relationship. This means that some relations may have durations of fewer than 30 days when they are replaced by an alternative relationship before the 30-day duration expires.

Both types of examples are illustrated in Figure 3.12, using the same sample data from Tables 3.7 and 3.8. In late 2015, for example, Libya's Haftar Faction and the Shura Council of Mujahideen in Darnah clashed twice in less than 30 days, resulting in a conflictual relationship

Figure 3.12
From isolated events to co-operative and conflictual relationships



Source: Authors.

between 1 September and 25 October. The same actors briefly clashed again in February 2016, before establishing an alliance, which translates into a conflictual relationship of 10 days, followed by a co-operative relationship of a maximum of 30 days. The opposite scenario occurs in late April, during which both parties briefly work together against the Islamic State before fighting each other for a longer period of time (Box 3.3).

Box 3.3
Data processing

Data processing steps were done using the open-source R software (R Core Team, 2019[55]) and a custom script that began with the list of ACLED events and the 30-day duration limit. The script records a tie for each pair of actors involved in an event that lasts 30 days from the date of the event. If the next event occurs but is beyond the 30-day duration, then the script simply records a new tie between the pair of actors that lasts 30 days. However, if the next event is within the 30-day duration and of the same type (oppositional or co-operative), then the tie duration is extended to last until 30 days after the new event. If the next event is within the duration limit but of a different type, then the original tie is interrupted by a new tie of the new type, even if the original tie had not yet reached the 30-day duration limit. The output of this script retains all relevant data from the original ACLED events, from their data identifiers, to information about the actors, to the geographic locations of the multiple events that can comprise the relationship.

Source: Authors.

Table 3.8
ACLED events transformed into pairs of actors

Event type	Event date	Actor X	Actor Y
Opposition	1 September 2015	Haftar Faction	Shura Council
Opposition	25 September 2015	Haftar Faction	Shura Council
Opposition	11 February 2016	Haftar Faction	Shura Council
Opposition	22 February 2016	Islamic State	Shura Council
Opposition	22 February 2016	Islamic State	Haftar Faction
Co-operation	*22 February 2016*	*Haftar Faction*	*Shura Council*
Opposition	20 April 2016	Haftar Faction	Islamic State
Opposition	20 April 2016	Shura Council	Islamic State
Co-operation	*20 April 2016*	*Haftar Faction*	*Shura Council*
Opposition	21 April 2016	Haftar Faction	Shura Council

Note: Co-operative events are indicated in blue and italic, oppositional events in red.
Source: Authors, based on data from ACLED (2020[47]), *The Armed Conflict Location & Event Data Project*, https://acleddata.com/data-export-tool/.

KEY METRICS FOR CONFLICT NETWORKS

The goal of this report is to map alliances and rivalries between violent organisations, assess how these relationships change over time and evaluate the effects of military interventions on their social patterns (Table 3.9). To address these questions, this study develops a novel approach to assess how structurally important each violent organisation is in the region and what the overall architecture of the conflict environment is in which violent organisations operate.

The study also relies on a series of simple metrics that measure how alliance and rivalry networks change over time, particularly with respect to foreign military interventions.

To measure how key properties that describe the efficacy of a network change over time at the node level, the study considers the total number of ties that an organisation has within a given unit of time, also known as temporal degree centrality (Table 3.10). In a co-operation network, actors

Table 3.9

Questions and approaches to assessing social networks

Research questions	Approaches
1) Who is allied with whom? Who is in conflict with whom?	Assess the structural importance of violent organisations (centrality) and topology of the entire network (centralisation)
2) How do conflict networks change over time?	Assess signed network change statistics (density)
3) How do military interventions affect conflict networks?	Assess the impact of interventions on signed network change statistics (density, centralisation)

Source: Authors.

Table 3.10

Selected metrics

	Positive ties	Negative ties	Positive and negative ties
Node	Temporal degree: Number of actors an organisation collaborate with within a given unit of time (Falzon et al., 2018[54]).	Temporal degree: Number of actors an organisation is in opposition with within a given unit of time (Falzon et al., 2018[54]).	PN centrality: Structural importance of an organisation simultaneously connected to allies and enemies (Everett and Borgatti, 2014[30]).
Network	Network density: Proportion of co-operative ties actually present in the network during a specified time interval. Network centralisation: indicates whether the network is more or less centralised around a few key actors.	Network density: Proportion of opposition ties actually present in the network during a specified time interval. Network centralisation: indicates whether the network is more or less centralised around a few key actors.	No existing joint measure

Source: Authors.

with high temporal degree centrality have many allies, which enhances their structural importance in a network. An increase in centrality over time means more alliances between actors. In an opposition network, actors with high temporal degree centrality have many enemies. An increase in centrality over time means that actors have an increasing number of enemies.

Signed networks are typically encoded as separate matrices where negative and positive relations are recorded as negative numbers (e.g. –1) and positive numbers (+1), respectively. This might imply that negative networks are conceptually simply the inverse of a positive network. However, because negative networks tend to have different structural forms than do positive networks, most measures designed around the structural patterns of positive relations are difficult to interpret and apply (Everett and Borgatti, 2014[30]). This is especially true for metrics that are based on concerns about reachability, flows and influence, such as betweenness or closeness centrality that measure how an organisation can work as a bridge between disconnected parts of a network and how far an organisation is from the centre of the network, respectively. For this reason, there have only been a few metrics that have been developed specifically for negative networks. Fewer still address the problems of a combined set of positive and negative relations.

Positive and negative networks conceptualise power differently, and the literature characterises two different approaches to power: power-as-access and power-as-control (Smith et al., 2014[44]), as mentioned above. Positive networks are associated with the power-as-access perspective and negative networks with power-as-control. Though separate metrics have been developed for each type of network, the development of metrics that bridge both interpretations for a mixed network comprised of both positive and negative relations has only recently occurred. This is the logic behind the development of the Positive-Negative centrality measure (Everett and Borgatti, 2014[30]). This metric was developed for mixed signed networks and captures both aspects of power in a joint centrality measure. The PN centrality measure reflects both the ideas that positive ties contributes positively to an actor's influence and that negative ties diminish it (Bonacich and Lloyd, 2004[56]). Actors connected to many well-connected allies or who have few negative ties to central others will have higher PN scores.

At the network level, this study considers density, which represents the number of ties actually present in a network divided by the number of ties that could potentially exist, and network centralisation, which indicates whether the network is centralised around a few key organisations. A high density of co-operative ties means that the network contains large political or military coalitions. A temporal increase in density can either mean that there are fewer violent actors in the conflict and/or that actors have more collaborative ties between them. A high density of conflictual ties means that the network contains few coalitions and many clusters of actors in conflict. If density increases over time, it means that there are more violent actors and/or that actors have more conflictual ties between them. To distinguish between the two situations, the report considers the total number of actors as an additional metric (Table 3.10). A similar logic applies to network centralisation.

The creation and disappearance of nodes and ties is a powerful, albeit simple, way to assess whether the overall number of parties involved in a network tend to expand or contract. Density provides crucial information about the temporal evolution of networks: sudden increases in density means that actors are increasingly involved in violent confrontations or building more alliances between each other, depending on the variable considered to study the network. There is no joint measure of density for signed networks that can capture both positive and negative ties.

These metrics are applied to foreign military interventions, regarded as the introduction of foreign actors that use force into an existing conflict. The study first identifies if and to what extent an intervention tends to modify the patterns of alliances and conflict in which local actors are already embedded. The study then detects changes in the co-operation and opposition networks that can be attributed to a military intervention using the PN centrality.

Four main types of external actors are taken into consideration: intergovernmental organisations such as the United Nations and NATO; regional bodies such as the Economic Community of West African States (ECOWAS), the military forces of nation-states from other continents such as France and the United States, and the military forces of African countries acting outside their own territory. Some of the interventions are still ongoing or have lasted for years (OECD/SWAC, 2020[48]) Therefore, for each intervention, it is necessary to identify one or several time periods during which military operations were conducted that would have had a direct impact on insurgents on the ground.

This study focusses on three military interventions that have significantly affected the conflict environment of the region: 1) the French-led intervention in Mali since 2013 that initially aimed at reasserting control over the north of the country (Operation Serval) and is now focussed on fighting jihadist organisations (Operation Barkhane); 2) the offensive of the Multinational Joint Task Force (MNJTF) initiated by Nigeria and the surrounding countries in the Lake Chad region in 2015 against Boko Haram; and 3) Operation Unified Protector launched by NATO in 2011 in Libya, which began as a humanitarian intervention to protect civilians during the Arab Spring and ultimately led to the end of the Gaddafi government (OECD/SWAC, 2020[48]).

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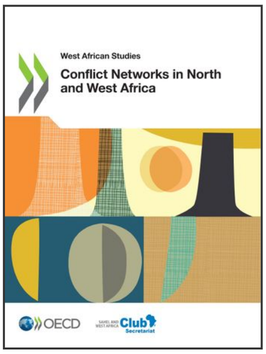

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