Fall 2017

Scenarios of social conflict dynamics on duplex networks

Miron Kaufman
Sanda Kaufman, *Cleveland State University*
Hung T. Diep

Scenarios of social conflict dynamics on duplex networks

Miron Kaufman
Department of Physics
Cleveland State University
Cleveland, OH.44115, USA

Sanda Kaufman
Levin College of Urban Affairs
Cleveland State University
Cleveland, OH.44115, USA

Hung The Diep
Laboratoire de Physique Théorique et Modélisation CNRS UMR 8089
University of Cergy-Pontoise
France

Abstract

Social conflicts among large groups of people can have serious and costly consequences that can exceed the time and space boundaries of the contentious groups. They require carefully thought-out strategies for addressing the contested issues. However, the complexity of social conflicts poses obstacles to their resolution. Not only is it difficult to find clear cause-and-effect relationships, but the conflict dynamics impede prediction of outcomes. For any group in conflict, strategizing to find a way out requires an approach that allows testing of the range of consequences of various strategies. Thus in complex situations, where predicting how the opponent will respond to a strategy is difficult, a party to conflict might engage instead in anticipation, generating and preparing for a range of possible scenarios. We draw from duplex networks modeling to further analyze a recently proposed scenario-generating model of conflicts and illustrate its application with two examples.

I. Social conflict scenarios

Social conflict (e.g., Rubin & al. 1994) occurs among large groups of people who differ on specific issues that each group holds important, with interests driven by differing values and identities. It can be latent but frequently bursts in the open around joint decisions. At such decision points, conflicting social groups contend with each other. Conflicts around politics and consequential policies at the federal, state and local levels fall in this category, as do international disputes. The waging of conflict can be pursued peacefully through processes such as voting or negotiations; at times it can also descend into violence, both within and between countries. The peaceful decision processes are by no means necessarily friendly: members of the clashing groups can actively engage in persuading each other to their point of view in order to secure favorable outcomes.

Conflicts tend to be very different from each other despite some general similarities. For example, although environmental conflicts usually revolve around environmental issues, their location, time, political and social contexts, specific issues and participants make them both complex and rather unique. At the eye level of group members, interveners or observer, patterns and future directions are rather resistant to prediction and may appear chaotic. It is also difficult to foresee the outcomes resulting from the numerous decisions of interacting parties in time. The chaotic appearance at one observation level may look different at a higher level. At such a level we may no longer discern the detailed interactions but, as with other with other complex phenomena, we may distinguish patterns. Then it is possible to derive a range of possible social conflict trajectories, or scenarios.

When two groups are engaged in conflict, the web of interactions inside each group and between the groups can be represented as two interconnected networks. Inside each network and between them, the groups' members are nodes and the inter-node links are their interactions.

This approach, used in physics to study complex phenomena, is applied here to the study of complex social interactions. The utility of applying the network modeling approach to the study of social conflicts and generation of scenarios resides in the following notion: stakeholders to social conflicts need to foresee the unpredictable (Bonabeau 2002; Lempert et al. 2002).

To engage in a joint decision – where the outcome for all depends on the choices of many – conflicting parties need to prepare strategies contingent on their opponents' reactions. However, in complex situations with numerous individuals making interacting choices, such reactions are difficult to predict reliably enough to prepare responses. Therefore, it may be wiser for each party to abandon the quest for prediction and switch to anticipation. Instead of aiming to figure out what the opponent will do (equivalent to a point prediction), it is more feasible and helpful to anticipate a range of possible opponent reactions and prepare for that range instead of the point estimate (Lempert et al. 2002).

Underlying the anticipation approach is the idea that social conflicts occur within complex, interrelated physical and social systems. Decisions in such contexts are fraught with uncertainty. Unlike simple one-cause – one-effect relationships that can be understood and managed, social systems may yield some of the results sought, but often also a host of unforeseen and negative side-effects. To compound the difficulty, some decision consequences accrue fairly quickly while others take longer time to show results. For example, a change in tax policy at the federal or state level may yield some economic results fairly quickly; education policy changes may take longer to show results; some environmental policies may not show their consequences during the life-time of the decision makers.

Planners and ecologists faced with complex interacting social-ecological systems use scenarios to explore possible consequences of planning or management decisions (e.g., Butler et al. 2005; Cobb & Thompson 2012; Kriegler et al. 2012;). Physicists use toy-models to represent and study complex interactions (e.g, Marzuoli 2008). One method for generating possible conflict outcomes – or scenarios – is to construct a model that can be queried in what-if fashion to explore consequences of different conditions or of adopting various strategies. We combine the network approach from physics with the scenario technique from planning to examine the range of possible outcome of social conflicts. We begin with two groups and represent their interactions using a duplex network (two interrelated networks) model. We generate and explore scenarios of the interactions that differ in the assumptions about the values of a small number of parameters. Any of the two groups could then use the model to ask what-if questions that can help the group select a strategy that might be wise for a range of scenarios instead of just one predicted possibility. Conflict strategies that cover a range of possible outcomes are considered robust (Lempert et al., 2002; Lempert et al. 2006), as opposed to fragile ones relying on point predictions.

We propose to illustrate the potential of network models to anticipate outcomes of social conflict dynamics through scenario generation. We begin by outlining a duplex network model, drawing the correspondence between elements and relationships of a two-group social conflict and some physics concepts that can be studied on networks. Then we show how the duplex network model can be applied to explore various conflict scenarios, using two recent social conflict confrontations – the 2016 “Brexit” referendum and the 2016 presidential elections in the United States. In our examples the outcome is already known. However, when the model is applied to a conflict before the outcome has materialized, it can provide scenarios that a group can use to devise or alter its strategy in response to the dynamic at work and anticipated outcomes. The advantage of such outcome scenarios over other analyses that can inform strategy is that it parsimoniously offers a global perspective on possibilities.

II. Model

We consider two groups in conflict. In each group, each individual has a preference regarding how the conflict should be resolved. Each individual has an attitude s (corresponding to spin in physics) with respect to a specific conflict. In group 1, individuals' attitudes range from -M1 (very open to negotiating some agreement) to M1 (inclined to protracted conflict due to adherence to extreme positions consistent with one's ideology). Similarly, in group 2, individuals' attitudes range from -M2 to M2. Here for illustrative purposes we consider M1 = M2 = 3.

Members within each group are networked: they interact with each other. Each individual acts with a certain intensity (energy in physics) to persuade others in the group to his/her point of view and is subject to others' persuasion efforts. We assume that each individual interacts with all other individuals inside his/her own group as well as with individuals in the other group. The pattern of interconnections corresponds to two Renyi-Erdös equivalent neighbor networks, a configuration with links of equal strength among all nodes.

Our model of the individuals' interactions within each group and between the groups yields averages of the individual preferences at any time t. Each network (group) has its own average value: s1 and s2 respectively. The in-group intensity (energy) of advocacy of an individual from group 1 is –J1*s*s1 while the corresponding energy of an individual in group 2 is: –J2*s*s2, where s1 is average of all s in group 1 and s2 is the average of all s in group 2. To reflect the effects of mutual persuasion, the inter-group intensity of interaction (energy) of any individual is taken to be proportional to the product between the individual's preference s and the mean value of the preferences of the other group's members: K12*s*s2 for an individual in group 1, and –K21*s*s1 for an individual in group 2.

Given the individuals' preferences at time t, the Boltzmann probability distribution of the preferences s at time t+1 for each group is proportional to the exponential of the intensity of interactions (energy):

$$\rho 1(s, t+1) = \frac{e^{s(J1s1_t + K12s2_t)}}{\sum_{s=-M1}^{M1} e^{s(J1s1_t + K12s2_t)}}$$
$$\rho 2(s, t+1) = \frac{e^{s(J2s2_t + K21s1_t)}}{\sum_{s=-M2}^{M2} e^{s(J2s2_t + K21s1_t)}}$$

Since persuasion is not instantaneous, we assume the interactions between the individual preferences s at time t + 1 and the collection of individuals from the two groups to be lagged, with the averages s1 and s2 evaluated at an earlier time t. ρ1(s, t) and ρ2(s, t) yield the fractions of all individuals who have preference s at time t, in group 1 and group 2 respectively. We (Diep, Kaufman, Kaufman 2017) have proposed this model and presented some of its predictions concerning the time evolution of the mean attitudes s1 and s2. Here we concentrate on the time evolution of the distribution of attitudes.

III. Examples

To illustrate how this model can offer some insight into the dynamics of social conflict, we show a couple of implementations that attempt to model two relatively recent events with a two-group structure: "Brexit" and the 2016 US elections. In-depth political analyses are intellectually satisfying in that they seem to link causes and effects that "make sense" to us. However, as in the two examples we describe, such analyses can miss the big picture. We would argue that both types of analysis are needed and that our simple model can contribute valuable input to strategists on each side.

Brexit

In the Brexit case, Group 1 was composed of the British government and supporters of continued membership in the European Union (EU); group 2 contained individuals who wanted to exit the European Union. The case was characterized by time oscillations, with the pro- EU group and the pro-Brexit group alternating in leading in polls at different times. We chose relatively high values for J1 and J2, with K12 <0 and K21 > 0 to obtain similar oscillations sustained in time. In terms of the interactions between the two networks, K12 < 0 reflects that the extreme (uncompromising) wing of the pro-Brexit Group 2 encourages pro-EU Group 1 members to be accommodating, while the moderate (compromising) wing of Group 2 fuels the extreme wing of Group 1. K21 > 0 means that extreme wing of Group 1 strengthen the extreme wing of Group 2, while the moderate wing of Group 1 helps Group 2 moderates. This is shown in the graphs of Figure 1, where: J1 = J2= 0.25, K12 = -0.1, K21 = 0.1.

Before the Brexit referendum, we could explore various outcome scenarios that could result from these patterns. For example, we assume that those who prefer to remain in the EU for staying in Europe are members of Group 1 whose preferences s range from 3 to -2, as well as those in Group 2 who are most accommodating, with s = -3. The rest (Group 1 members with s = -3 and Group 2 members with s from 3 to -2) would rather break away from the EU.

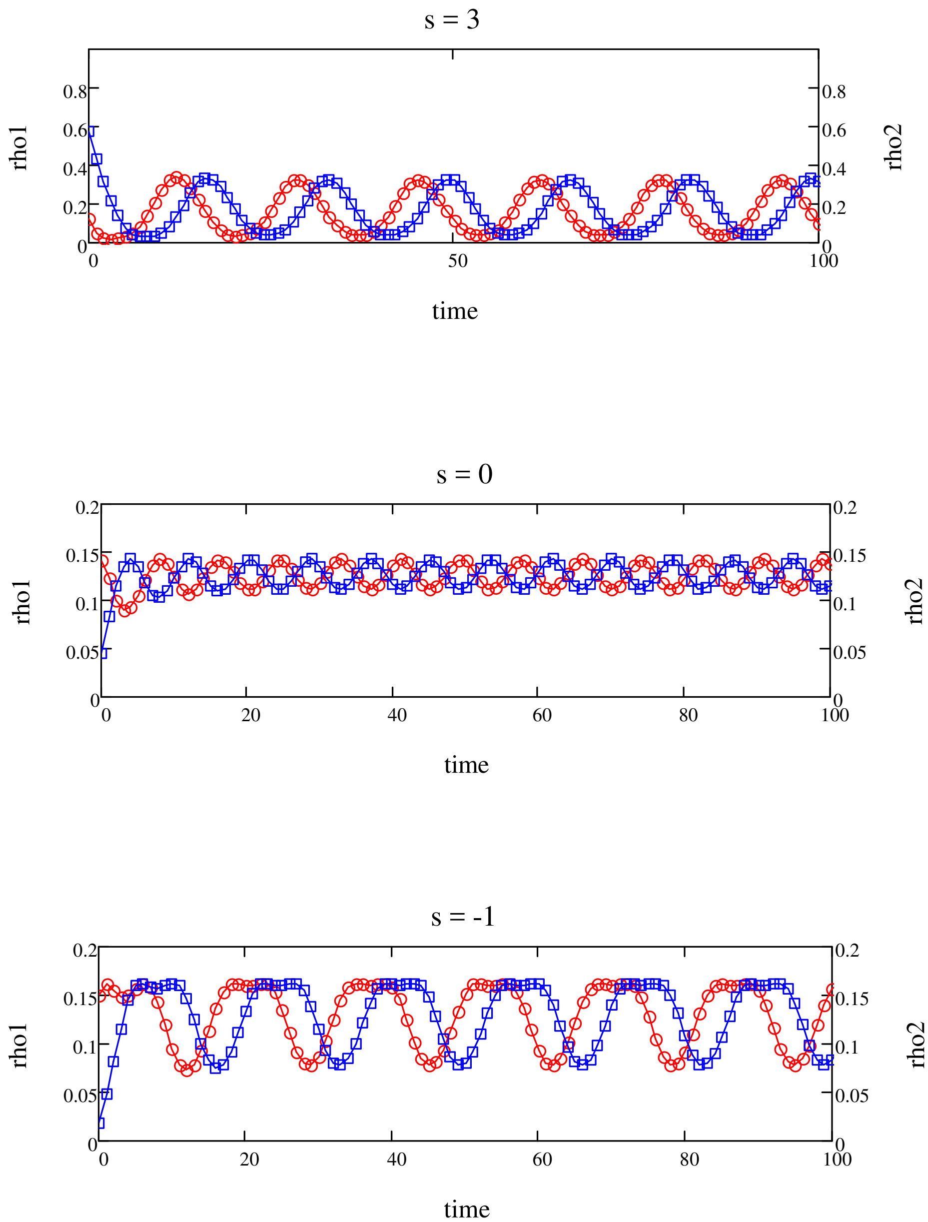


FIGURE 1: Time oscillations of the attitudes s = 3, 0, -1.

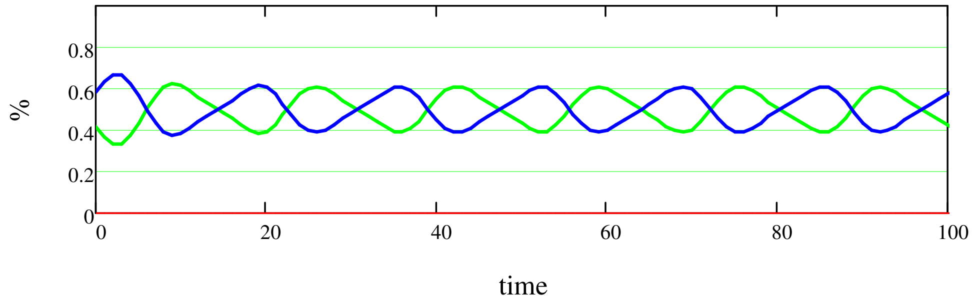


FIGURE 2: Time oscillations of fractions of EU supporters and Brexit supporters. In this scenario everyone votes.

In another possible Brexit scenario, Group 1 members with preferences s from 3, to -2 prefer to stay in the EU; Group 2 members with preference values s between 3 and -2 would rather break away; members of both groups whose preference value s = -3 are disengaged and do not vote. Here is the outcome in this scenario:

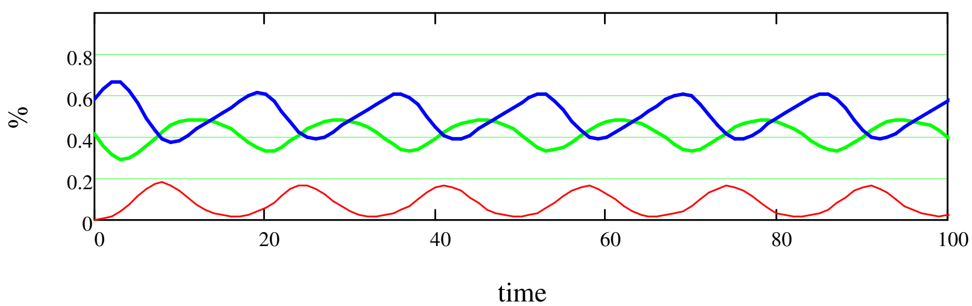


FIGURE 3: Time oscillations of fractions of EU supporters and Brexit supporters. Lowest curve corresponds to the non-voters.

US presidential elections, 2016

Next we simulate the dynamics leading to the outcome of the 2016 US elections. Republicans are Group 1 and Democrats are Group 2. In our model, Democrats are more cohesive than Republicans: J2 > J1; they influence Republicans more than Republicans influence them: K12 > K21. The results below were obtained for: J1 = 0.25, J2= 0.3, K12 = 0.1, K21 =

0.02. In Figure 4 we show the time evolution of the non-compromising attitude s = 3 and of the compromising attitude s = -3.

We consider a couple of scenarios. In the first scenario (Figure 5), those in Group 1 whose preferences s range from 3 to -2 are likely to vote for the Republican candidate. Similarly, in Group 2 those with preferences s ranging from 3 to -2 vote for the Democratic candidate. In both groups, those whose preference s = -3 either do not vote (they are not sufficiently engaged) or they vote for a third candidate. In this scenario, the Republican candidate wins the elections.

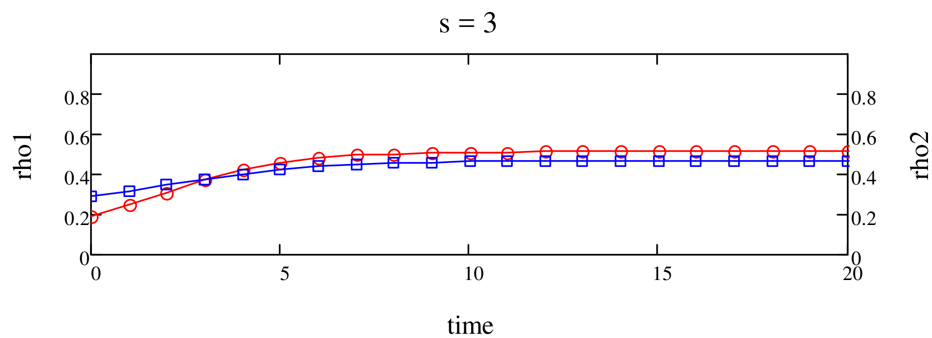
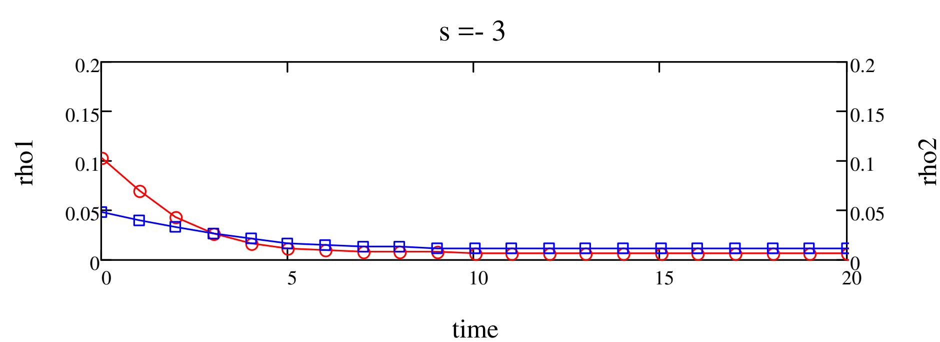


FIGURE 4: Time evolution of the attitudes s = 3 and -3.



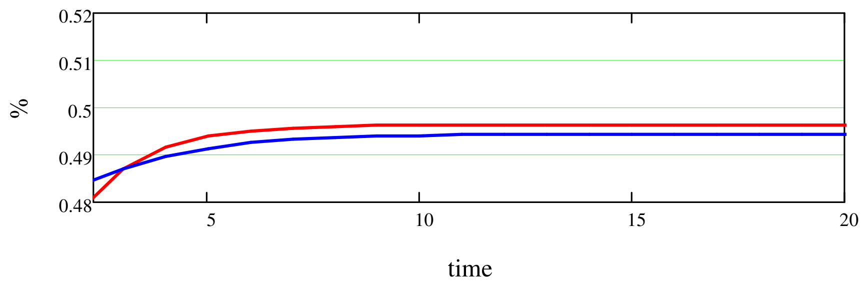


FIGURE 5: Time evolution of fractions of democrats and republican supporters. In this scenario the attitude s = -3 in both groups either do not vote or vote for third party.

In the second scenario (Figure 6) those in both groups with preference s = -3, whom we could view as independents groups, vote for the Democratic candidate. As a result the democrats win the election.

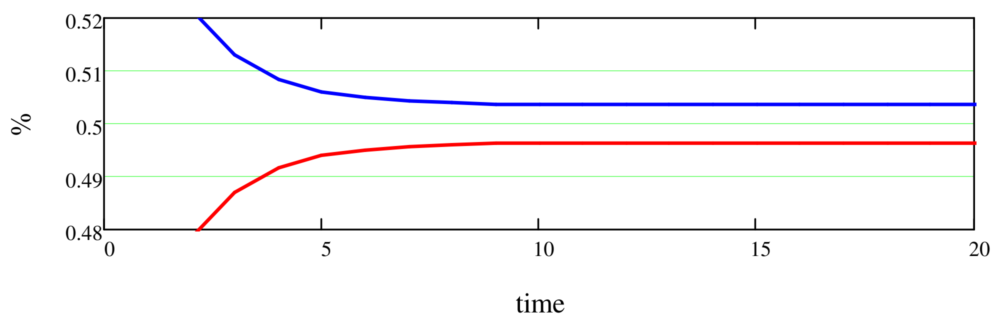


FIGURE 6: Time evolution of fractions of democrats and republican supporters. In this scenario the attitude s = -3 in both groups votes for the democrats.

IV. Conclusions

We have used a model for generating anticipatory scenarios to be used by parties in two-group social conflict to devise strategies. We have shown how distributions of attitudes inside each group and their time evolutions can be derived, to gain insight into possible group choices. We have illustrated in two examples – 2016 “Brexit” referendum and US elections – how such a model can be used to analyze real two-group conflicts.

REFERENCES

Bonabeau, E. (2002). Predicting the unpredictable. *Harvard Business Review*, *80*(3), 109-116.

Butler, C. D., Corvalan, C. F., & Koren, H. S. (2005). Human health, well-being, and global ecological scenarios. *Ecosystems*, *8*(2), 153-162.

Cobb, A. N., & Thompson, J. L. (2012). Climate change scenario planning: a model for the integration of science and management in environmental decision-making. *Environmental Modelling & Software*, *38*, 296-305.

Diep H. T., Kaufman M., Kaufman S. (2017) *Dynamics of two-group conflicts: A statistical physics model,* Physica A, volume 469, Pages 183-199.

Kriegler, E., O'Neill, B. C., Hallegatte, S., Kram, T., Lempert, R. J., Moss, R. H., & Wilbanks, T. (2012). The need for and use of socio-economic scenarios for climate change analysis: a new approach based on shared socio-economic pathways. *Global Environmental Change*, *22*(4), 807-822.

Lempert, R., Popper, S., & Bankes, S. (2002). Confronting surprise. *Social Science Computer Review*, *20*(4), 420-440.

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A general, analytic method for generating robust strategies and narrative scenarios. *Management science*, *52*(4), 514-528.

Marzuoli, A. (2008). Toy models in physics and the reasonable effectiveness of mathematics. In *Deduction, Computation, Experiment* (pp. 49-64). Springer Milan.

Rubin, J. Z., Pruitt, D. G., & Kim, S. H. (1994). *Social conflict: Escalation, stalemate, and settlement*. Mcgraw-Hill Book Company.