FORECASTING POLITICAL INSTABILITY:

CONTROL-THEORETIC MODELING OF INTERNATIONAL CONFLICT

by

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ABSTRACT

FORECASTING POLITICAL INSTABILITY:

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Forecasting political instability is an important research area because it can lead to less expensive and more accurate political analysis. This knowledge can then be used to interpret political behavior and guide policymakers' decision processes. The challenge is to create a tractable method that retains political meaning and preserves enough information of the underlying dynamic system so as to support the development of predictive models. We first discuss an external data analysis method that models the complex social system of international interactions. Then we describe two internal dynamics models and create our own model based on consensus protocols that is capable of showing stable disagreement. We verify this model by simulating the dynamics of the Israeli-Palestinian Conflict. Our model shows some promise of being an accurate representation of the computation mechanisms underlying complex social multi-agent systems.

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Chapter 1

Introduction

Political instability can be described as a time period when power and positions of those in government change enough to upset the status quo. Examples of this would include an incumbent party being voted out of office, a foreign invasion, or some other major transfer of power. In democracies, political instability is often marked only by raging op-ed pieces, localized strikes and marches, and other peaceful demonstrations. When political instability occurs in countries without established traditions of peaceful transitions between powerholders (non-democracies especially), there is an increased risk of violence, government failure, financial loss, and citizen suffering.

Forecasting political instability is about predicting future situations that will be marked by the characteristics explained above. The hope of forecasting political instability is that past data will be able to indicate behavior patterns in key political stakeholders (agents) that will be valid in the future. Examples of possible political agents include individuals, social groupings, institutions, and nations. Political instability can be forecasted by simulating how the current political situation will evolve and how the balances of power will fluctuate over time. Predictions often focus on the agents who will have the greatest effect in negotiations and power transfers. Training a model with past data to see if it properly forecasts what has already occurred will enable us to become more confident in our results; however, we will still lack a guarantee that the model will work for some present conflict whose end result is still unknown.

1.1 Motivation

Forecasting political instability is valuable because it results in accurate analysis and is less expensive than other policy-analysis efforts. Applying models and simulations of political interactions can result in a better understanding of how a situation will evolve and what are the likely outcomes of alternative actions. It is possible for forecasting results to lead nation states to better understand other strategic agents, key moments of change, and important areas of influence, allowing them to avoid costly mistakes. With this knowledge, pressure can be applied by policymakers to ensure a more peaceful transition of power.

When a political entity is aware of the best option, it is more likely to make correct decisions; however, if analysis results in inaccurate conclusions, the likelihood of political conflict can increase. Failures in analysis are directly responsible for some of the most dramatic political conflicts of the past century: Yom-Kippur War, the Cuban Missile Crisis, the fall of the Berlin Wall, and Weapons of Mass Destruction in Iraq. Traditional political analysts are susceptible to certain cognitive errors that have contributed to inaccurate conclusions. Intense conflicts, like the Israeli-Palestinian Conflict, are often colored by emotion, making it difficult for policymakers to be unbiased. Control-theoretic modeling forecasting political instability is an attempt to be less prone to group think, primacy effect, recency effect, bounded rationality, dissonance, attribution theory, prospect theory, rigid standard operating procedures, and bureaucratic politics by finding the true dynamics of the system. A data-driven forecasting model can achieve valuable analytical results while avoiding these cognitive errors if it accurately models the international conflict.

A data-driven forecasting model is also valuable because it can overcome or alleviate the challenges of having many qualified, experienced, and capable strategic analysts. It would also lessen analysts' physical and moral burdens of making important decisions with life-and-death consequences [18]. A system that accurately forecasts political instability would be less expensive than hiring the many strategic analysts that are currently used.

1.2 Modeling Approaches

This thesis discusses two main theoretical approaches to forecasting political instability: external data analysis methods and internal dynamics models. External data analysis methods create artificial mappings between inputs and their associated outputs by finding patterns in the data. While this can result in a methodology that has predictive power, it provides limited insights into how the system actually works. The results can still be used to adapt inputs to reach a certain output, but the actual internal dynamics are not revealed and thus, the ability to apply pressure to certain agents, relationships, or coalitions by policymakers would be limited. Still, if an external data analysis method provides an accurate mapping of inputs to outputs that can be used to forecast political instability, it would suggest a certain relationship exists between the two that could be explored using an internal dynamics model.

Internal dynamics models focus on the actual inner structure of the system. A simple model is created to simulate the behavior of the relevant agents. Multi-agent systems, which endow each agent who is important to the political situation with the ability to interact with other agents, are a useful model type. The model's parameters are then calibrated to fit the inputs and outputs. This method results in a greater understanding of the internal dynamics and thus provides insights not only into the reachability of outputs but control of the system.

The goal of creating an internal dynamics model to forecast political instability is to discover the symbolic equations that explain the dynamics that are observed in an international conflict. Similar to how Newton's Laws can be used to accurately predict the behavior of mechanical systems, we are trying to use consensus dynamics to find the "Newton's Laws" that govern the interactions of political systems. We use consensus dynamics because these describe how people change their positions on issues based on whom they interact with.

1.3 Modeling Challenges

In this work, we are addressing a validation problem. It is difficult to validate our results due to the irreproducibility of political events, agent subgroup specification, and difficulty of application, even with a well-designed model. While we attempt to overcome these challenges, these issues represent weaknesses in our work.

1.3.1 Irreproducibility of Political Events

Unlike other modeling applications, the inability to reproduce international conflict events is an inherent weakness and obstacle to verification. There is no control, no duplication, and no experimentation. While some similarities between events may exist, factors such as leadership transitions, alliance shifts, location developments, and differences in time make each event unique. Due to human memory, even a hypothetically perfect repetition of an event could have a different effect – remembering that an agent is repeating a certain action can affect the impact of the second occurrence.

1.3.2 Agent Subgroup Specification

Both modeling approaches described in Section 1.2 face the problem of agent subgroup specification. Which groups matter most and need to be included as agents in the model needs to be determined. The goal is to find the simplest model that still describes the behavior of the actual agents fairly well. At any level, there are internal dynamics that make a more specific agent beneficial and external dynamics that make a more general agent beneficial (a person could be argued to be too generic and a country too complex). The goal of aggregation is to separate agents with opposing viewpoints into different agent subgroups, while incorporating agents with similar and consequential geography, political loyalties, religious views, and languages into a coherent subgroup.

Constancy, how much an agent subgroup loses or gains agents, is desirable in order to simplify the system. The challenge is that agents change position over time and could move enough to warrant a different subgroup specification. Agent subgroups should be created in a manner that retains a maximum level of constancy within subgroups by minimizing drastic agent position changes over time.

System identification can be used to determine the best agent subgroups. A collection of different agent subgroups is created in accordance with the economic, political, and cultural characteristics of the system. With data about how the system actually evolves, a metric is constructed to determine the difference between the simulated result and the actual result of the international conflict. Using the metric, the different combinations of groupings are compared, and the best is chosen.

With any model, there is a tradeoff between simplicity and accuracy. An overly simplistic model may be tractable, but the conclusions may lack predictive power; an overly complex model may have predictive power, but be intractable. This balance between simplicity and accuracy can arise in multiple areas, such as agent subgroup aggregation, variable specification, and parameter designation.

1.3.3 Difficulty of Application

After a model is created, another obstacle exists: those who actually determine political policy often are not willing to apply an empirical mathematical model for important policy decisions. Some fear the rigidity, others the lack of control or lack of accountability; many simply do not trust a system that appears to disregard the efforts of thousands of hours of training of thousands of researchers and analysts around the world. This is an important issue because if the model results do not influence policymakers, then the model is simply an exercise.

1.4 Contributions of this Work

In a search for an underlying law explaining the social system interactions of international conflict, this thesis compares two different approaches to modeling. We develop two models using consensus dynamics for simulating international interaction dynamics that could lead to political instability: a linear position dynamic model and a nested network model. Our analysis of the linear position dynamic model addresses conditions for convergence and stability. The nested network model is created by incorporating nonlinear influence dynamics (one for intercoalitional influence and another for intracoalitional influence) and a network structure with a two-level hierarchy to the linear position dynamic model. While the linear and nonlinear components have been explored previously by [36] and [20], the coupling of these two protocols with different inter- and intracoalitional influences is new. Using a data set for the Israeli-Palestinian Conflict, we simulate the negotiation dynamics between 1987 and the Oslo Accords in 1993 to check the resulting system for predictive power. We analyze the visualization results for indications of political instability and for agent behavior that accurately reflect real-life events.

1.5 Literature Review

The models and results presented in this thesis bear strong resemblance to the literature of recent decades. While the actual equations were developed independently, the overall concept of the model was based off Bueno de Mesquita's work [4] [5] [6]. In his work, Bueno de Mesquita uses four parameters to describe the political behavior of an agent: influence, salience, firmness, and position. Although our model uses the same four parameters, our equations that describe how these values evolve are different. Our model's basic construction is quite similar to DeGroot's [11] model, but we add additional elements to the dynamics of the adjacency matrix. Our model relates to the consensus work of Chatterjee and Senata [10] and Friedkin and Johnsen [14].

There have been computational modeling projects simulating complex decision-making processes of large organization and bureaucracies from certain quantifiable signals by [7] [45] [30] [2] [31] [42] [22]. While our research has a unique focus on political instability, the negotiation processes of countries is very similar to those explored in these papers. A number of researchers have tried to represent political conflict with mathematical models: [38] summarizes the history and predicted future of quantitative methods based on political science theory used to create accurate prediction models for international relations.

A summary of basic social and economic network models is presented by Wasserman and Faust [47] and more recently by Jackson [25]. Axelrod [3] provides excellent examples of agent-based models with analysis through computer simulation and we use the same tool at the end of this thesis. Much of the literature incorporates game theoretic methods, such as Charness and Jackson [8] and Myerson [34]. Chatterjee, Dutta, Ray and Sengupta [9] use sequential interactions between agents, while we use simultaneous interactions. Our influence dynamics are similar to the bounded confidence model used by Hegselmann and Krause [20] to produce opinion fragmentation and polarization.

The linear position dynamic model we use is quite similar to Ofati-Saber and Murray's [36] Protocol A1, but we add terms to account for the other variables in an international conflict. DeMarzo, Vayanos and Zwiebel [12] present influence dynamics and position unidimensionality. Our research also relates to the social influence work by Friedkin and Johnsen [13] and Lopez-Pintado and Watts [28].

Researchers have applied consensus networks to economics and social systems (Slikker [41], Young [50], Jackson [25],and Lopez-Pintado [27]) and the spread of epidemics (Moreno [33], Newman [35]). Although focused on other applications, this thesis is related to other consensus work with similar mathematical formulations (Tsitsiklis, Bertsekas and Athans [46] and Krause [26]). Lorenz [29] addresses issues of stability, although in a different manner than done in this thesis.

The rest of the thesis is organized as follows: In Chapter 2, we explore an external data analysis method created by [23]. In Chapter 3, we describe an internal dynamics model for consensus network problems, built off the work of [5] and [36] . In Chapter 4, we simulate the nested network model from Chapter 3 to check how well it fits the literature and real-life events of the Israeli-Palestinian Conflict. Conclusions are presented in Chapter 5.

Chapter 2

External Data Analysis Method

2.1 Background

External data analysis methods search for patterns in data to associate certain inputs with their appropriate outputs. In order to accomplish this in this thesis' problem domain, rules are created in a manner that incorporates the backgrounds of the agents involved in the international conflict so that they fit possible theoretical events. Unless a researcher has an accurate understanding of the cultural, economic, and political characteristics of the agents, rules can force notions of patterns onto data (while excluding contradictory data as outliers), instead of extracting information from data. The following section analyzes in detail an external data analysis method. After reviewing its basic construction, we indicate areas that may be insufficient for creating a predictive model.

2.2 HSW and the EP Tool

Hudson, Shrodt and Whitmer (HSW) developed the Event Patterns Tool (EP Tool), a database manager and image creator which allows the user to analyze RSS newsfeeds for certain patterns based on specified actors, actions, and dates. The goal of the EP tool is to be "a methodology that is capable of preserving the agential basis of social interaction, capable of analyzing the rules behind such purposive behavior, capable of tracking multiple agents as they enact rules through behavior directed at one another, and capable of capturing the evolution of such interaction over time" [24]. Essentially, the EP Tool reads newsfeeds and reports the frequency of certain event patterns. The main body of their work applies the EP Tool to the Israeli-Palestinian Conflict.

2.2.1 Method Description

Having created action and agent dictionaries, HSW created a program that determined what the words appearing in each headline mean in the cultural context of the international conflict being modeled. Actions are delimited to a list of predetermined verbs that are divided into categories: verbal cooperation, material cooperation, verbal conflict, and material conflict. The agent dictionary delineates individuals, organizations, and coalitions from each other by placing them into unique subgroups. In their analysis, HSW combine all agents into two major coalitions: Israeli and Palestinian. HSW use a counter to see how many times certain agent-verb-agent combinations occur in AP article headlines and displays the occurrences on a histogram. The purpose of creating these visualizations is to be able to discern certain patterns in the international conflict. These patterns can indicate when political instability is likely. The EP Tool serves as a useful visualization method of the Israeli-Palestinian Conflict, but is susceptible to certain shortcomings, which are explained in the following subsection.

2.2.2 Method Analysis

Aggregation

HSW's method of aggregation has several key benefits. First, although the most active agents in the Israeli-Palestinian Conflict are few, they do not always respond to stimuli in an exactly reciprocating manner. For example, AIPAC (The American Israel Public Affairs Committee) could anger Hamas, which, although not willing to attack the USA, could attack Israel in response. By aggregating AIPAC and Israel, analysts would appropriately see Hamas' action as a response to provocation.

Aggregation can have mixed effects on agent subgroup specification. Combining individual agents into subgroups increases continuity over the transition of leaders and political parties that are ideologically equal. Aggregation also works well for accounting for the many different nouns that can be used in reporting a single agent (Hamas, Gaza City militants, Palestinians, refugees, etc); however, it also places agents who often have completely opposing viewpoints (Palestinians, the PLO, the Palestinian Authority, Hamas, Fatah, Islamic Jihad, etc) into the same subgroup. This also confuses those who have true influence on the decisions and actions pertinent to the conflict, and those who are simply observers. Agent aggregation results in an inflated frequency of interactions because instead of rare actions between many agents, the EP Tool would detect many actions between few agents.

In applying the EP Tool, if all agents are aggregated into two large subgroups, some important agents are excluded. In the Israeli-Palestinian Conflict, other states have a major impact in peace negotiations and in major military excursions. Although they were often the excuse for Arab military invasions, Palestinians were not the main opposing forces in six major wars which involved Israel: the War of Independence (1948), the Sinai War (1956), the Six-Day War (1967), the Yom Kippur War (1973), the First Lebanon War (1982), and the Second Lebanon War (2006) [40]. Only in the smaller, less organized, sporadic, but still deadly, conflicts (such as the First and Second Intifadas and the recent Gaza War) was the fighting mainly between Israelis and Palestinians. Since the interactions with other nations have major ramifications on the conflict, by ignoring the surrounding states as actors, the EP Tool could miss major cooperation and conflict events.

Rules and Patterns

There is an issue with assigning cause-and-effect relationships between two events that are reported in the AP headlines for the same time period. Israel may change its policy, not in response to some outside Palestinian pressure, but simply because after an election a new political party takes control of the Knesset. This occurred when Benjamin Netanyahu followed Shimon Peres as Prime Minister in 1996 and instituted a “tit-for-tat” policy for responses to Palestinian suicide attacks in Israel. Despite the real cause for change lying within the Israeli-coalition, the EP Tool would categorize this action as material cooperation and look for a Palestinian provocation causing the change in policy.

Understanding the agents using this external data analysis method is difficult because there are many reasons to explain a matching set of inputs and outputs. For example, during a certain application of the EP Tool, HSW claim that an offering of peace (an Olive Leaf) was offered in the middle of a “tit-for-tat” sequence. They claim that this nested pattern took on the meaning of “You have the choice about which of our actions to reciprocate. You can reciprocate the violence, or you can reciprocate the peace. And then we will follow suit” [24]. Decreasing control over negotiations seems to conflict with political theory, where agents seek to create incentives for others to act a certain way – not to give them choices. Three other valid explanations for this nested behavior are: the agent is trying to confuse the other agents about its intentions; an agent is trying to appease one party (the international community) by offering peace, while appeasing another party (their own constituents) by sending aggressive, non-conciliatory messages; there are different agents with opposing agendas placed within a single agent subgroup (an error of aggregation).

Combining all events into two broad categories, the EP Tool can be ignorant of an event's severity: a Palestinian youth throwing a rock at an IDF soldier could be treated the same as a Hamas militant firing a rocket at Sderot. Similarly, permanent changes (new laws, settlement construction, etc) could be treated with equal weight as temporary changes (military checkpoints, visa restrictions, etc). If the effect of an event does not disappear unless a canceling event occurs, then it should affect the position of an agent more than events whose effect diminishes over time. Although the emotions of the agents in the events may match, the opportunity cost of the culprit and the damage to the victim can be quite different, and this should be reflected in the external data analysis method.

Applying the EP Tool to any conflict requires timing and threshold issues to be properly considered. Some of the EP Tool's patterns and rules appear to be based on Western, and not Semitic, cultural norms. For example, in one analysis, the researchers assume that after a week, each agent has forgotten the others' actions. However, "Islamist[s] can be seen to display great patience. The patience is there for the planning of terrorist operations that can take years to bring to fruition and with it its sense of vigilance...Islamist adversaries...expect their 'wars' to last decades, or, indeed, however long it takes" [44]. In the Israeli-Palestinian Conflict, an agent acting after a weeklong pause is not necessarily a provocation, but can easily be in response to an action that occurred more than seven days before.

The application of a week-long window also ignores the intergenerational issues of the Israeli-Palestinian Conflict. For many of the issues, such as right-of-return, borders, and citizenship, ancestors' actions affect descendants. Although occurring decades later, an action in 1998 could be the direct response to an insult from 1948. Imposing time lengths for pauses and provocations can lead to innacuracies when analyzing conflict between groups in the Middle East.

Thresholds are introduced into the HP Tool in order to distinguish background noise from signals and these are also susceptible to overlooking the true nature of the agents. HSW designate four Israeli material conflict events in a six day period below which no signaling would be apparent to the other side; and for the Palestinians, a threshold of two material conflict events in a six day period. Material cooperation was rare, so there was no threshold [24]. By this rule, five attacks in six days sends a signal to the other side, but four attacks in six days does not. In order for these artificial thresholds to make sense, the Israelis would have to be more sensitive than the Palestinians so they react sooner and the Palestinians would have to be thicker skinned, so they need six events in order for them to realize that Israel is attacking. This does not match the history of the Israeli-Palestinian Conflict. Assigning frequency-time ratios for distinguishing noise from signals is difficult because each agent in this conflict closely monitors the words and actions of the other side. While some events are of so little importance that they do not merit a response, there is no arbitrary number where they become significant.

Data

Although they are readily available, there are challenges to using news headlines as a data source. HSW assume that since the Israeli-Palestinian dyad has been the focus of sufficient media attention, "the event data are a reasonably accurate description of the actual behavior in the system"; however, radical ideas are rarely published in the mainstream media, and undercoverage and stereotypical reporting are not abnormal [23]. Due to "ownership, the pressure of advertising, the relations among media, business, and government, and the process of news production," there can often be a strong bias in the media [16]. Some criticize modern reporting because of its dependence on wire sources, which use press releases, easy-to-locate officials, media handlers and focus only on the same institutions and sources [16]. Media's role as a gatekeeper and an agenda setter makes it particularly vulnerable to bias and suggests that it should not be the trusted metric for forecasting political instability with an external data analysis method. Herman and Chomsky conclude that media employees choose stories that conform to acceptable themes because they are too distracted by the financial attraction to cheap, convenient official sources; they fear negative responses from groups that might threaten their dominant position; and they need to satisfy the desires and biases of their advertisers [21]. The idea of media being objective and balanced is not a safe assumption for HSW's EP Tool.

Another issue with using AP headlines is duplicity of reporting. The data is passed through a one-a-day filter in order to eliminate duplicate reports of the same event by allowing only one instance of any source-event-target combination in a day [24]. While duplicity is a problem that needs to be addressed, the filter HSW implement leads to a loss of detail and causes three errors. First, if two similar events were to occur in one day, only one would be counted. Depending on which event-headline passed the filter, there could be differences in severity and intelligence. The media could report one group did the attack, but later in the day find out another did it and correct the report. The new headline would count as another attack, instead of a correction of the previous event-headline. Second, if an attack were very severe, then there would be multiple headlines about the attack for days afterwards and this filter will let those pass through and be counted because they were reported on a different day, even though a new event did not occur. Major conflict and cooperation events will be counted more than minor conflict and cooperation. Third, ambiguous English grammar with different word orderings could result in a confusion between the source agent and target agent of an event.

Not using this filter might correct for the lack of a severity metric. A major event would receive more coverage and each unique headline would be counted – resulting in additional counts in the EP Tool. A sensationalized issue may get over-coverage, but that is the story that gets more public attention and has a greater effect on the public, causing the event to have a greater impact.

The ideal periods of analysis cover dates that are reported from the same source with minimal agent morphing. Analysis that looks at a window that required more than one data source would have different press biases, audiences, agendas, vocabularies, reporting densities, and corporate pressures.

Verbal communication carries heavy significance in Middle Eastern cultures where symbolic words can begin and end wars. Not only is verbal communication important, but it is used in a very different way by Semites than by Westerners.

> "The adult Arab makes statements which express threats, demands, or intentions, which he does not intend to carry out but which, once uttered, relax emotional tension, give psychological relief and at the same time reduce the pressure to engage in any act aimed at realizing the verbalized goal... Once the intention of doing something is verbalized, this verbal formulation itself leaves in the mind of the speaker the impression that he has done something about the issue at hand, which in turn psychologically reduces the importance of following it up by actually translating the stated intentions into action...

> There is no confusion between words and action, but rather a psychologically conditioned substitution of intention (especially when it is uttered repeatedly and exaggeratedly) achieves such importance that the question of whether or not it is subsequently carried out becomes of minor significance." [37]

While this can cause confusion and ambiguous interpretations with Westerners, there should be less misunderstanding between Israeli and Palestinian coalitions.

2.3 Summary

In summary, an external data analysis method would have more success properly describing the international conflict if it accounted for the severity and evanescence of each event. Issues of timing and thresholds are also be important. Finally, unique regional issues related to media bias and communication should be taken into consideration. If these features are accurately accounted for, an external data analysis method can be expected to more accurately forecast political instability. These issues, while pertinent to external data analysis methods, are not as critical in the internal dynamic model described in the following chapter.

Chapter 3

An Internal Dynamics Model for Consensus Network Problems

3.1 Background

Internal dynamics models seek to represent the inner workings of a complex system using a simple model. By looking for the actual causal mechanisms in an international conflict, we hope to accurately forecast political instability. While the external data analysis methods lack any knowledge of the structure of the system, the internal dynamics models identify the inputs and outputs and then attempt to identify the laws that connect them. The goal is to create a mathematical representation that can be used to gain additional insights into agent behavior and to create accurate forecasting of events.

Internal dynamics models often are composed of multi-agent systems where agents are individuals or groups that are conceptualized as decision makers whose choices depend on their own states and the states of others. This is compatible with rational-actor theory, which assumes that people weigh benefits to costs before making decisions. The goal is to create a model that maps states to decisions so that the system can be simulated knowing only the current state variables. In contrast to the EP Tool that is susceptible to inaccuracies in measures of severity, evanescence, timing and threshold issues, the linear position dynamic model and the nested network model that are presented in this chapter do not depend on these issues. Nevertheless, these models will suffer from inaccuracies in the hypothesized agent structure and interagent dynamics (which we will assume arise from consensus seeking behavior).

After reviewing two examples, this chapter will present the foundational concepts of consensus network problems. Then, we present a linear position dynamic model. After discussing certain properties of this model, we present nonlinear influence dynamics and a network hierarchy structure. Finally, these two elements are incorporated into the linear position dynamic model to create a nested network model.

3.2 Two Related Modeling Examples

3.2.1 Operational Net Assessment

The first example is when the American military used a straightforward methodology to explore a system's internal network structure. The United States Joint Forces Command (USJFCOM) created the Operational Net Assessment (ONA), which "was a formal decision-making tool that broke the enemy down into a series of systems - military, economic, social, political - and created a matrix showing how all those systems were interrelated and which of the links among the systems were the most vulnerable" [17]. ONA is a simple system that explains the basic internal structure of an international conflict [19]. This analysis tool "provides joint force commanders extensive information in advance of a crisis, leading to actionable knowledge and decision superiority that facilitate the effective application of diplomatic, economic, informational, and military power" [48]. With an emphasis on unconventional warfare, this system is appropriately focused on the type of conflict and dangerous situations that exist today.

3.2.2 Bueno de Mesquita

For our second example, we describe Bueno de Mesquita's internal dynamics model that takes a conflict, extracts a specific question, and predicts what will happen. He identifies key stakeholders who have influence on the outcome and then predicts how important leaders will act in the negotiation process. Dismissing the theory of some disembodied national interest, he models nations as "leaders trying desperately to stay in power by building coalitions within their selectorate". They do this by "buying off cronies in the case of a dictatorship, for example, or producing enough good works to keep *hoi polloi* happy in a democracy" [43]. He assumes that the major players only care about the outcome and who gets credit for the outcome [5].

This method identifies important actors but does not aggregate them into agent subgroups. Bueno de Mesquita consults experts to find out what each agent wants, how focused they are, how much influence they have, and how stubborn they are. He tries to find hidden solutions where leverage could be employed to create friendly coalitions or to weaken enemy coalitions by properly aligning incentives with a desired outcome in surprising or overlooked situations.

After determining which agents to include in his model, Bueno de Mesquita assigns values between 0 and 100 for each agent's position, influence, salience, and firmness. The position of an agent is a measure of what outcome the agent wants concerning a certain issue; the issue is defined on a linear spectrum with two extremes. The influence of an agent is how much one agent is followed by the other agents. The salience of an agent is how important the issue is to that agent. The firmness of an agent is the stubbornness of that agent. Then he sorts the agents according to their desires and analyzes possible coalitions. Using a game-theoretic simulation, agents' positions are allowed to change depending on other agents' positions. This process is repeated, agents gravitate to equilibrium positions, and the game continues until a coalition is strong enough to make and implement the decision. In the end, Bueno de Mesquita reviews possible simulation paths and concludes which is the most probable outcome.

This method is valuable because it is focused directly on political instability. By modeling a negotiation process in an international conflict, Bueno de Mesquita is searching for conditions that will result in a change in the balance of power. Although there are certain limitations to the complexity that can be addressed (every tangled conflict must be condensed into a single, independent issue), Bueno de Mesquita only uses resources that are easily available and which can be verified by applying the model to past situations, such as news reports, regional publications, and expert interviews.

Although this method works holistically and, he claims, in practice, there are issues of robustness. If only a small shift at the beginning causes a great change in the final result, then the initial conditions must be known accurately in order for the resulting analysis to be useful. Unfortunately, with political issues, there is not always an easy scale between 0 and 100 that defines each position. Instead, the values chosen are often arbitrary and they could be varied slightly without being inaccurate. Although initial conditions are often important, Bueno de Mesquita's model is especially susceptible to error because there is no strict definition that specifies agents' position, influence, salience, or firmness value.

3.3 Consensus Network Problems

Consensus network problems have attracted attention in recent years with applications in multiple fields, as specified in Section 1.5. While we use many of the traditional formulations, terminology, and definitions from the literature, we have introduced unique variations for the analysis of international conflict. We propose that political agents change their positions based on other agents they are forced to interact with due to identity (e.g. being political parties of the same legislative body) and who they choose to interact with (two groups who have the same position on an issue). We begin by describing the basic construction of a consensus network problem and then we present the linear position dynamic model. After presenting nonlinear influence dynamics and network structure, we add these to the linear position dynamic model to create the nested network model.

3.3.1 Basic Construction

First, we explain the basic terminology and definitions of a consensus problem network. We borrow heavily from [36].

Let (V, E, A) be a graph of order n. It is described by the set of nodes (agents) $V = [\upsilon_1, ..., \upsilon_n]^T$, the set of edges $E \subseteq V \times V$, and a weighted adjacency matrix $A = [a_{ij}]$, with nonnegative adjacency elements a_{ij}. The node indices belong to a finite index set $I = \{1, 2, ..., n\}$. An edge is denoted by $e_{ij} = (\upsilon_i, \upsilon_j)$. The adjacency elements associated with the edges of the graph are positive (i.e. $e_{ij} \in E \Leftrightarrow a_{ij} > 0$) and they describe the position and influence dynamics.

The values of a_{ij} depend on the values of four variables that are defined for every agent: position (P_i), influence (Φ_i), salience (S_i), and firmness (F_i). The position of an agent is a measure of what outcome the agent wants concerning a certain issue.

The issue is defined on a linear spectrum with two extremes. The influence of an agent describes how much one agent's position affects the position of other agents. The salience of an agent is how important the issue is to that agent. The firmness of an agent is the stubbornness of that agent. Although people might quantify each of these parameters slightly differently, we assume that they would agree with the relative ordering and the dynamics should qualitatively match even if the numeric values slightly differ. These four parameters are given by:

$$P_i \in \mathbb{R} : 0 \leq P_i \leq 100, \text{ with } P = [P_1, ..., P_n]^T \tag{3.1}$$

$$\Phi_i \in \mathbb{R} : 0 \leq \Phi_i \leq 100, \text{ with } \Phi = [\Phi_1, ..., \Phi_n]^T \tag{3.2}$$

$$S_i \in \mathbb{R} : 0 \leq S_i < 100, \text{ with } S = [S_1, ..., S_n]^T \tag{3.3}$$

$$F_i \in \mathbb{R} : 0 \leq F_i < 100, \text{ with } F = [F_1, ..., F_n]^T \tag{3.4}$$

We recognize that political systems have varied and complex levels (people can form agents, factions, parties, coalitions, nations, etc.), but in our model we will focus on only two methods of aggregation: neighborhoods and coalitions. How agents are grouped together is important because it affects how agents influence each other – specifically, neighborhoods will be used in the nonlinear influence dynamics and coalitions will be used in the inter- and intracoalitional influences.

A neighborhood is defined for each agent as the set of agents whose position values are within some neighborhood radius ϵ. For an agent υ_i, its neighborhood can be denoted as $N_i = \{\upsilon_j \in V : |P_i[k] - P_j[k]| < \epsilon\}$. While neighborhood is defined by position, a coalition is defined by something different than position that affects how agents will influence each other.

A coalition, C_j, is defined as a subset of agents that have a unique influence relationship, no matter what their position may be. A model has w coalitions and the integer n_j is the index of the last agent in a coalition C_j. Thus, the set of agents $\{\upsilon_1, ..., \upsilon_n\}$

can be partitioned to show the coalitions as follows: $\{\upsilon_{n_0}, ..., \upsilon_{n_1}, \upsilon_{n_1+1}, ..., \upsilon_{n_2}, ..., \upsilon_{n_w}\}$, where $\{\upsilon_{n_{j-1}+1} ... \upsilon_{n_j}\} = C_j$. By this definition, each agent is in one and only one coalition.

In order to clarify the difference between neighborhood and coalition, consider political parties within a country. A political party would be a neighborhood and the country would be a coalition. Two parties in the same country who disagree on an issue would be in different neighborhoods but the same coalition. Two parties in different countries who agree on an issue would be in the same neighborhood but different coalitions.

Two nodes, υ_i and υ_j, *agree* if and only if $P_i = P_j$. *Consensus* is achieved when $P_i = P_j \ \forall \ \upsilon_i, \upsilon_j \in C_i$ and such a point is called a *position agreement value* for that coalition. When the model achieves consensus, we want the position agreement value to somehow describes the international compromised settlement for a real political negotiation or interaction on a particular issue (for example, the Oslo Accords, the Nuclear Non-Proliferation Treaty, the Kyoto Protocol, or the Treaty of Lisbon). This value can be determined by analyzing official declared agent positions and any negotiated settlements between the key stakeholders in the conflict.

Using the format from social network research in [11] and [36], we will represent the linear agent position dynamics in the form $P[k+1] = AP[k]$, where $k = \{0, 1, ...\}$ is the time period. We use discrete time, since even though opinions and positions are continuous, they are only reported, shared, and acted upon in discrete time. Every node is connected by an edge to every other node (i.e. $a_{ij} > 0 \ \forall i, j$). Our nonlinear influence dynamics are similar to those in [20] and are of the form $P[k+1] = A(P[k], t)P[k]$. The adjacency element a_{ij} are precisely the weights of this graph A. These two discrete equations provide the general equation form for our dynamic systems of equations.

3.3.2 Linear Position Dynamic Model

Consider the following system that describes the linear position dynamics for an n-agent system:

$$\begin{bmatrix} P_1[k+1] \\ \vdots \\ P_n[k+1] \end{bmatrix} = \begin{bmatrix} 1-\alpha_1\Phi_1-...-\alpha_1\Phi_n & \alpha_1\Phi_2 & \cdots & \alpha_1\Phi_n \\ \alpha_2\Phi_1 & 1-\alpha_2\Phi_1-...-\alpha_2\Phi_n & \cdots & \alpha_2\Phi_n \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_n\Phi_1 & \cdots & \alpha_n\Phi_{n-1} & 1-\alpha_n\Phi_1-...-\alpha_n\Phi_{n-1} \end{bmatrix} \begin{bmatrix} P_1[k] \\ \vdots \\ P_n[k] \end{bmatrix} \tag{3.5}$$

$$\begin{bmatrix} y_1[k] \\ \vdots \\ y_n[k] \end{bmatrix} = \begin{bmatrix} P_1[k] \\ \vdots \\ P_n[k] \end{bmatrix} \tag{3.6}$$

where $\alpha_i = a\frac{(100-S_i)(100-F_i)}{100*(n-1)}$; $\alpha_i\Phi_i = 0$; and Φ_i, S_i, and F_i are constants given by (3.2)-(3.4) with scaling constant a. Notice that each row of the A matrix has the following form:

$$P_i[k+1] = P_i[k] + \alpha_i \sum_{j=V\setminus\upsilon_i} (P_j[k] - P_i[k])\Phi_j[k] \tag{3.7}$$

Initially, these position dynamics may appear confusing. Agents move more towards an agent that is farther away than one that is closer because the change from round to the next depends on the difference in position between the two agents. Given agents υ_j,υ_k,υ_i with all things but position being equal, P_i moves closer to P_j than P_k if $(P_j[k] - P_i[k]) > (P_k[k] - P_i[k])$. One explanation of the proportion of the change is that when two agents are close, one does not need to move far towards the other in order to appease the other's demands – a small movement has a decent payoff. When agents are far apart, only large position shifts are signals of changing positions. Thus, in order to please another agent, greater movement occurs.

Stability Analysis

Theorem 1. *The linear position dynamic given by (3.5) are marginally stable if $a < 0.0001$.*

Proof. If $a < 0.0001$, then the A matrix defined in (3.10) is positive and row-stochastic, since $0 \leq S_i < 100$ and $0 \leq F_i < 100$. Then, the Perron-Frobenius theorem states that the largest eigenvalue of A will be 1 [39]. Therefore, all other eigenvalues are such that $|\lambda_i| \leq 1$, and the discrete-time system is at least marginally stable. □

While political stability refers to the constancy of power by an agent or coalition; this stability analysis specifically refers to when the states of the agents find equilibrium. Thus, even though the system is stable, an event of political instability may occur if the system's equilibrium represents a change in power with respect to the system's initial condition.

Convergence Analysis

Theorem 2. *All equilibria for the linear position dynamic given by (3.5) occur when every agent in the model has the same position agreement value (i.e. when $P_i = P_j \ \forall \ \upsilon_i, \upsilon_j$).*

Proof. Since the dynamics of the linear position system are discrete, an equilibrium can be described as when $P[k+1] = P[k]$. This condition is satisfied when $P[k] = AP[k]$. Since A is row-stochastic, the only solution to this equation is when

$$P = p \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}, \ \forall \ p.$$

□

In international negotiations, consensus does not always occur. Thus, the linear position dynamic model given in (3.5) is insufficient for representing real phenomenon because it lacks the capability of displaying stable disagreement. This suggests that we should modify the model. In order to be able to model stable disagreement, we construct nonlinear influence dynamics that, when implemented in a two-level hierarchy, will allow for coalitions to have different position agreement values but also be stable (i.e. $P_{C_i}[k] \neq P_{C_j}[k]$ but $P_{C_i}[k+1] = P_{C_i}[k]$ and $P_{C_j}[k+1] = P_{C_j}[k]$).

3.3.3 Nonlinear Influence Dynamics

Consider the following equation that describes nonlinear influence dynamics for an agent υ_i:

$$\Phi_i[k+1] = \Phi_i[k] + d(\gamma[k]\xi_i[k] - (100 - \gamma[k])|P_i[k] - \eta[k]|) \tag{3.8}$$

where V_i is the set of all agents υ_j such that $i \neq j$ and $|P_i[k] - P_j[k]| \leq \epsilon$; d is a scaling constant; $\gamma[k]$ is the overall level of clustering, $\xi_i[k]$ is the neighborhood strength, and $\eta[k]$ is the average weighted position with each respectively defined as follows:

$$\gamma[k] = \frac{\sum_{i=1}^{n} |P_i[k] - \eta[k]|}{n} \tag{3.9}$$

$$\xi_i[k] = \sum_{j=V_i} \frac{\Phi_j[k]}{100} \tag{3.10}$$

$$\eta[k] = \frac{\sum_{i=1}^{n} (P_i[k] \frac{\Phi_i[k]}{100})}{n} \tag{3.11}$$

In the linear position dynamic model (3.5), an agent's influence is modeled as a constant. In (3.8), it is a state variable with its own dynamics. We use two different theories for how an agent's influence can change. First, if an agent's position is near other agents' positions, then its credibility increases and consequently its influence increases. We measure the credibility of an agent by the number of agents whose positions are within the neighborhood radius of the agent's position. Second, since the average position of all agents is perceived as the most popular position, we decrease the influence of an agent if it is farther from this average position.

The variance of all of the agents' positions determines the magnitude of the impact of the two theories on an agent's influence. Using a measure of clustering ($\gamma[k]$) to describe the level of variance, we construct a convex combination to incorporate these two elements: if there is a high level of clustering ($\gamma[k]$), the credibility ($\xi_i[k]$) affects influence more than the distance from the popular position ($P_i[k]-\eta[k]$); if there is a low level of clustering, the distance from the popular position affects influence more than the credibility of an agent ($\gamma[k]$, $\xi_i[k]$, and $\eta[k]$ are defined in (3.9)-(3.11)).

3.3.4 Network Hierarchy Structure

Consider the following three equations that describe the position dynamics, intercoalitional dynamics, and intracoalitional dynamics within a network hierarchy structure for an agent υ_i:

$$P_i[k+1] = P_i[k]+\alpha_i \sum_{j\in C_1\setminus \upsilon_i} (P_j[k]-P_i[k])\Phi_{jA}[k]+\alpha_i\delta_{1,2}\sum_{j\in C_2}(P_j[k]-P_i[k])\Phi_{jB}[k]+\ldots$$

$$+\,\alpha_i\delta_{1,w}\sum_{j\in C_w}(P_j[k]-P_i[k])\Phi_{jB}[k] \tag{3.12}$$

$$\Phi_{iA}[k+1] = \Phi_{iA}[k] + d[\gamma_A[k]\xi_{iA}[k] - (100-\gamma_A[k])|P_i[k]-\eta_A[k]|] \tag{3.13}$$

$$\Phi_{iB}[k+1] = \Phi_{iB}[k] - d[\gamma_B[k]\xi_{iB}[k] - (100-\gamma_B[k])|P_i[k]-\eta_B[k]|] \tag{3.14}$$

where $\upsilon_i \in C_1$; and $\delta_{i,j}$ is a constant between 0 and 1.

These equations show two developments: first, we differentiate between intracoalitional influence (Φ_{iA}) and intercoalitional influence (Φ_{iB}); second, we adjust the linear position dynamic to incorporate these different influences and different levels of trust depending on whether two agents are in the same coalition or not. The difference between intracoalitional influence and intercoalitional influence is that the first saturates to 100 as time progresses while the second decreases to 0 as time progresses. At the beginning of the simulation, each agent's intercoalitional influence value is equal to its intracoalitional influence value ($\Phi_A[0] = \Phi_B[0]$). This reflects the assumption that while at the beginning of a negotiation, agents are influenced by anyone, as time progresses, they pay more attention to those within their own coalition. Thus, agents within a coalition can have different influences on each other than agents in different coalitions.

The $\delta_{i,j}$'s represent how much one coalition affects another (the trust between coalitions or the amount of interactions one coalition has with the other). Thus, while each agent broadcasts two different influences (one for agents within its coalition and one for agents outside of its coalition), the $\delta_{i,j}$'s allow for different coalitions to pay different levels of attention to the same intercoalitional influence broadcast. It essentially creates two consensus systems: one within coalitions and one between coalitions.

3.3.5 Nested Network Model

We can now write the block matrix representation for the nested network model that was described in (3.12)-(3.14) for a system with n agents and w coalitions. There are $3n$ states, contained in $P[k]$, $\Phi_A[k]$, and $\Phi_B[k]$, which are each n-dimensional vectors.

$$P[k+1] = \begin{bmatrix} P_1[k+1] \\ \vdots \\ P_n[k+1] \end{bmatrix} = \begin{bmatrix} A_{11} & \cdots & A_{1w} \\ \vdots & \ddots & \vdots \\ A_{w1} & \cdots & A_{ww} \end{bmatrix} \begin{bmatrix} P_1[k] \\ \vdots \\ P_n[k] \end{bmatrix} \tag{3.15}$$

$$\Phi_A[k+1] = \Phi_A[k] + f(P[k], \Phi_A[k], \Phi_B[k]) \tag{3.16}$$

$$\Phi_B[k+1] = \Phi_B[k] + f(P[k], \Phi_A[k], \Phi_B[k]) \tag{3.17}$$

$$\begin{bmatrix} y_1[k] \\ y_2[k] \\ y_3[k] \end{bmatrix} = \begin{bmatrix} P[k] \\ \Phi_A[k] \\ \Phi_B[k] \end{bmatrix} \tag{3.18}$$

where A_{ii} is given by

$$\begin{bmatrix} 1-\alpha_{n_{i-1}+1}(\Phi_{n_{i-1}+1A}+...+\Phi_{n_i}A)-\sum J_{n_{i-1}+1} & \cdots & \alpha_{n_{i-1}+1}\Phi_{n_iB} \\ \alpha_{n_{i-1}+2}\Phi_{n_{i-1}+1B} & \ddots & \alpha_{n_{i-1}+2}\Phi_{n_iB} \\ \vdots & \ddots & \vdots \\ \alpha_{n_i}\Phi_{n_{i-1}+1B} & \cdots & 1-\alpha_{n_i}(\Phi_{n_{i-1}+1A}+...+\Phi_{n_iA})-\sum J_{n_i} \end{bmatrix}$$

where $\alpha_i\Phi_i = 0$ and $\sum J_{n_k} = \sum_{j\in\{1...w\}\setminus i} \delta_{n_k,j}(\Phi_{n_{j-1}+1B} + ... + \Phi_{n_jB})$; and A_{ij} is given by

$$\begin{bmatrix} \delta_{i,j}\alpha_{n_{j-1}+1}\Phi_{n_{i-1}+1B} & \cdots & \delta_{i,j}\alpha_{n_{j-1}+1}\Phi_{n_iB} \\ \vdots & \ddots & \vdots \\ \delta_{i,j}\alpha_{n_j}\Phi_{n_{i-1}+1B} & \cdots & \delta_{i,j}\alpha_{n_j}\Phi_{n_iB} \end{bmatrix}$$

This nested network model does not have the susceptibilities to inaccuracies due to issues of severity, evanescence, timing, or thresholds, as the EP Tool has. This system incorporates elements that appear to match how organizations make decisions in real-life, but, this model has weaknesses. Media bias could result in inaccurate subgroup specification and coalition assignments. Although the dynamic equations for how an agent's position and influence evolve appear to agree with the literature, it is possible that certain agents follow protocols that are different.

The next chapter presents simulation results to show how the nested network model is useful for forecasting political instability because when we use the initial conditions from real data, we reach a position agreement value that is an appropriate representation for the actual negotiation settlement. Also, the model can result in varied behavior that is observable in international interactions. Thus, despite the weaknesses of the nested network model, we hypothesize that it is a step in discovering the “Newton’s Laws” that explain the social dynamics that create political instability.

Chapter 4

Consensus Simulation

This chapter is composed of three section that focus on the simulation results of the nested network model presented in (3.15) - (3.18). The first section describes some of the general behavior of the nested network model that is apparent from the simulation graphs. The second section discusses three simulation results that can indicate political instability. The third section applies the nested network model to initial conditions from the Israeli-Palestinian Conflict in 1987 and compares the simulated results with the negotiated agreement from Oslo in 1993 and political events in between.

4.1 Model Behavior

Graphs displaying the evolving positions of the agents are used for verification against values in the literature and in real-life. An issue is chosen with a defined spectrum between two extremes, represented by the real numbers between 0 and 100. An agent is assigned a position value between 0 and 100 that accurately represents the agent's belief about the issue. Similarly, values between 0 and 100 are determined for each agent's influence, salience, and firmness.

The visualization of the simulation displays only the positions of each agent as time progresses. Agents' positions are graphed on the vertical axis, with each line's intercept located at the initial value. Time is on the horizontal axis – a series of integers following the number of rounds. While such a discrete system does not represent the real-life continuous changing of salience, influence, firmness, and position, the exact values for these four variables only matter when the agents meet. By modeling the meetings of the agents, which may occur at regular or irregular intervals, this model is in agreement with the theoretical structure of international conflict negotiations.

An example of the simulation results of the nested network model (3.15) - (3.18) are presented in Figure 4.1. With 11 agents in total, the first six agents are in one coalition and the last five are in another. The initial conditions of this simulation are as follows:

$$P[0] = \{85, 85, 70, 70, 60, 30, 25, 20, 20, 0, 0\}, \Phi_A[0] = \Phi_B[0] = \{85, 85, 60, 100, 100, 60,$$

$$100, 70, 100, 20, 10\}, S[0] = \{85, 90, 50, 99, 80, 75, 95, 85, 95, 95, 80\}, F[0] = \{97, 97, 96,$$

$$98, 98, 96, 98, 97, 99, 96, 95\}, \epsilon = 10, d = .002, a = .000001, \text{and } \delta_1 = \delta_2 = .8.$$

The graph shows 11 lines, each showing how the positions of one of the 11 agents changes over time. It is evident from the slopes of the lines how quickly agents change positions. Once all agents have stopped moving, the simulation ends. While in this simulation, $\delta_{i,j} = \delta_{j,i}$, if they were not equal, the position agreement value would be attracted more to the extreme position of the coalition that pays the least attention to the other coalition.

It is unreasonable to assume that all of the coalitions eventually completely agree on an issue; however, they can get close enough that if a resolution was proposed between them that the coalitions would agree. If the position agreement values for

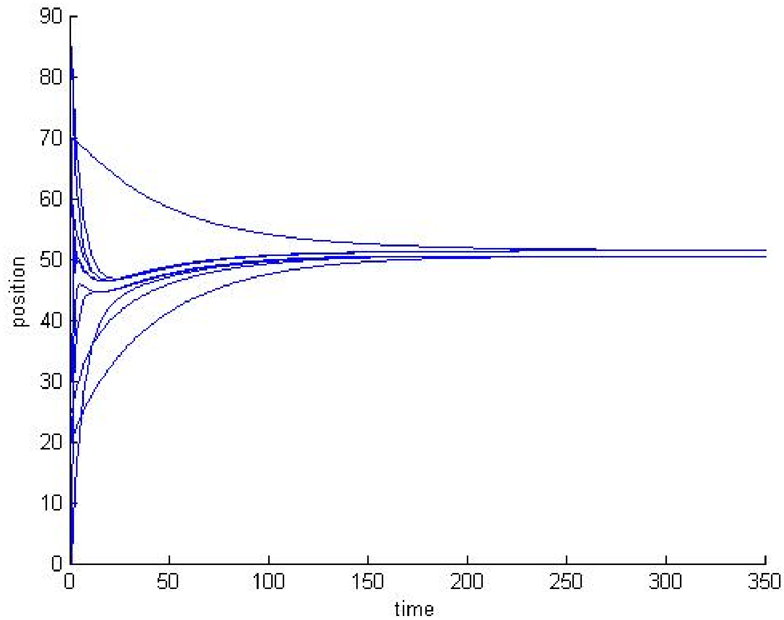

Figure 4.1 Example Simulation

the coalitions are too far apart (greater than ϵ), then a resolution on the issue would be difficult; however, if the position agreement values are close, then they should come to a negotiated settlement for the conflict. In Figure 4.1, the position agreement values of the coalitions are quite close, so a negotiated settlement value of 50 would be agreeable to both parties.

4.2 Simulation Graphs and Political Instability

Three different graphical results would indicate an increased likelihood of political instability. They are determined by analyzing how the initial average weighted position ($\eta[k]$) changes over time; looking for areas where consensus is reached by the majority of a coalition but the positions of other agents remain far apart; and looking for areas where the positions of the majority of all agents are close but then move farther apart. These three patterns suggest the possibility for a change in the ruling

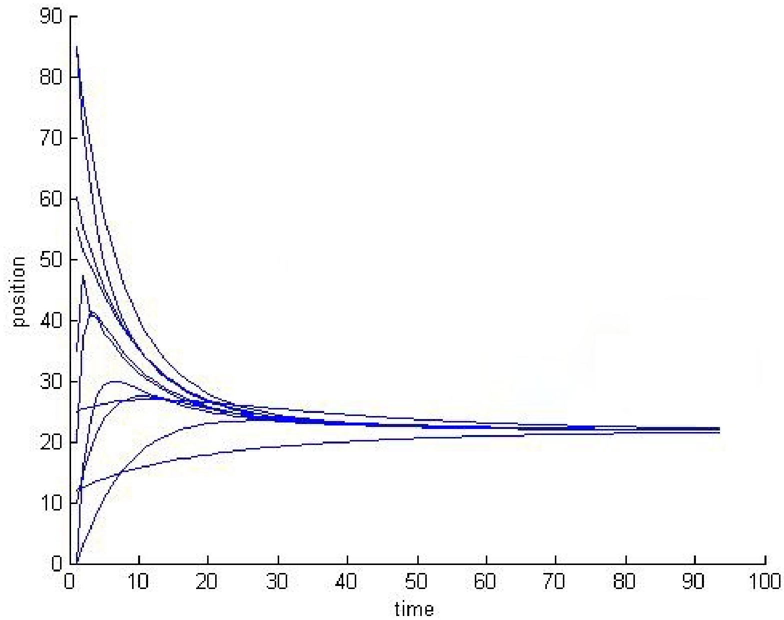

Figure 4.2 Change in Ruling Party

party, the change of coalition makeup, and diminished likelihood of a negotiated settlement after some time, respectively. All three of these situations would be described as political instability.

4.2.1 Change in Ruling Party

Political instability describes the time period when one party loses majority support to another party. This is observable when the average weighted position ($\eta[k]$) shifts from a position near the incumbent to the position of a challenging agent or when the incumbent is no longer the only agent near $\eta[k]$. Figure 4.2 shows the dynamics of the nested network model (3.15) - (3.18) with the following position and influence initial conditions and average weighted position: $P[0] = \{85, 85, 60, 55, 35, 25, 20, 12, 10, 0, 0\}$, $\Phi_A[0] = \Phi_B[0] = \{85, 85, 80, 100, 60, 100, 60, 100, 70, 20, 10\}$, and $\eta[0] = 49$.

With the greatest influence, agent v_4 ($P_4[0] = 55$ and $\Phi_{4A}[0] = \Phi_{4B}[0] = 100$)

could be the incumbent party, leading the coalition of agents $\{\upsilon_1, \upsilon_2, \upsilon_3, \upsilon_4, \upsilon_5, \upsilon_7\}$. Although the average weighted position remains around 50 for the first five rounds, as time progresses, $\eta[k]$ decreases, eventually reaching values in the 30's and 20's. This represents a change in the majority of opinion on the issue. While it is possible that the incumbent party could project a change in position and remain in power, it is no longer the only agent whose position is near to the average weighted position. Also, the intracoalitional influences of all of the agents increases over time and eventually saturates at 100. Therefore, the initial advantages of being highly influential and at the most powerful position are lost. It is likely that another party could try to take power. Such a political change would definitely be characterized as political instability.

4.2.2 Coalitional Change

Another situation that would indicate political instability is when the majority of agents in a coalition reach consensus except for a minority of agents whose positions are very different. Such a situation would suggest that a negotiated settlement could be achieved if the disagreeing agents were removed from the coalition, but also suggests that if the disagreeing agents are powerful enough, they may take action. Figure 4.3 shows an example of the nested network model (3.15) - (3.18) showing this possible coalitional change.

At the beginning of the simulation, most agents have different position values concerning the issue. While some quickly change position, others take a long time. Notice how the agents in the top coalition reach consensus near position 50 by time 20, except for the topmost agent. This extreme agent, whose position begins at 100, does not agree with the other members until after time 180.

If the disagreeing agent were removed from the coalition, then a negotiated settle-

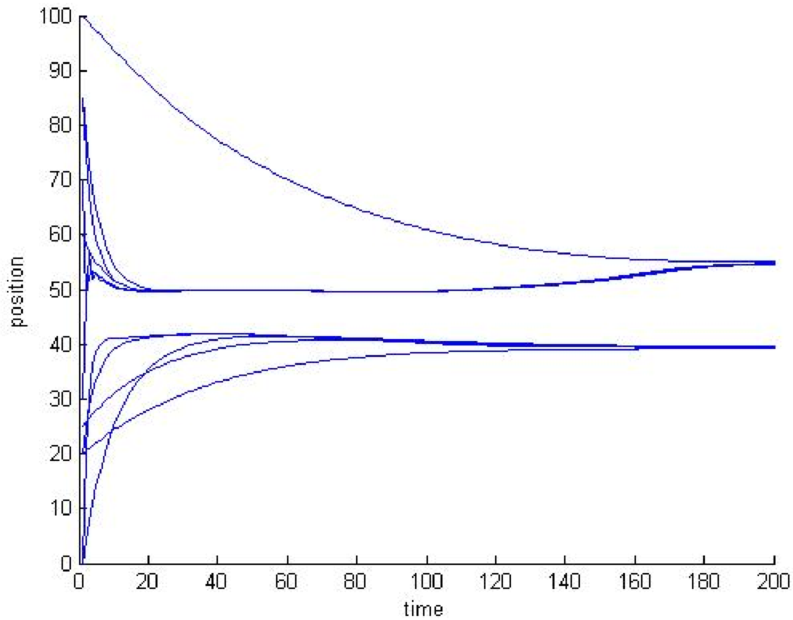

Figure 4.3 Coalitional Change

ment could occur sooner. If an agreement between coalition was more important to a coalition's agents than having every agent agree, then they may choose to remove the disagreeing agents from their coalition in order to prevent a longer conflict. This change can occur as long as the disagreeing agent does not have some sort of veto-power or other crucial attribute. It is quite reasonable to assume that a number of agents could believe that placating outside enemies is more important than placating interior extremist groups.

If the disagreeing agents are the most powerful agents, it is also possible that they will not be pleased with the rest of the coalition agreeing at a position value so far from its own. Having a few agents so far from the rest of the agents in a coalition could result in political contention, a coup by the disagreeing agents, or some other change in government power – all examples of political instability.

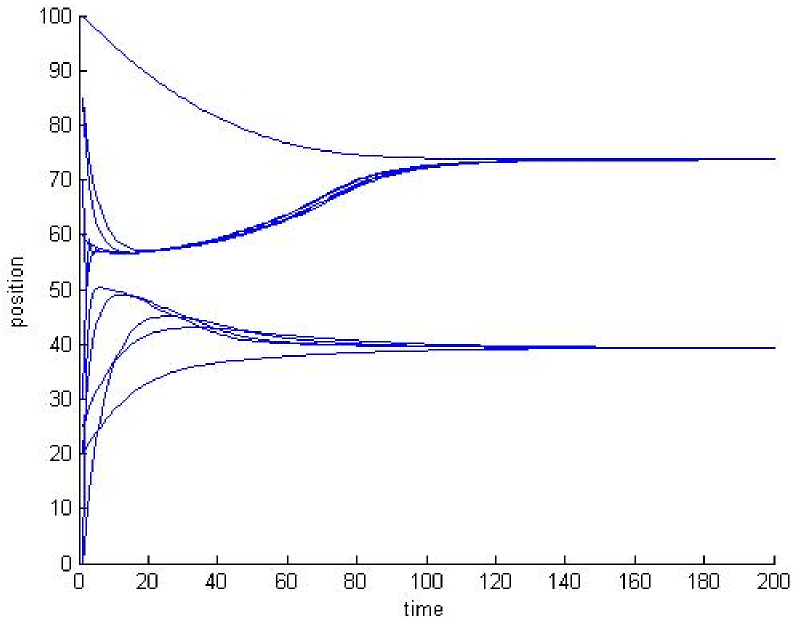

Figure 4.4 Attraction and Bifurcation

4.2.3 Attraction and Bifurcation

In some simulations, if given enough time, all of the coalitions reach some position agreement value, and those values are relatively close; however, it is possible that this never occurs. If the position agreement values are too far apart, any possible negotiated settlement would not be agreeable to all of the coalitions and the conflict would not end – a sign of future political instability. Figure 4.4 contains a simulation of the nested network model (3.15)-(3.18) where the coalitions reach very different position agreement values.

While such a result would indicate the possibility of long term disagreement and increased political instability, it also contains a trend that is encouraging. Figure 4.4 indicates that the coalitions approach each other as intercoalitional influences remain strong but then eventually bifurcate as intracoalitional influences become strong while intercoalitional influences diminish. With the knowledge that the coalitions will only drift farther away, if a negotiated settlement had been proposed early, then it is possible that they could have reached an agreement instead of waiting for full consensus within the coalitions.

In Figure 4.4, if a negotiated position had been suggested around value 52 between time periods 20-40, a majority of the agents would have been within ϵ – close enough to support the settlement decision. After this time, the coalitions drift farther apart. Eventually, the distance between their position agreement values becomes so large, that any proposed negotiated settlement value for the issue would not be agreeable to both parties. Aware of the impending division, policymakers could try to influence coalitions to agree to a settlement earlier in order to prevent the bifurcation and resulting long-term political instability from occurring.

4.3 Case Study: Israeli-Palestinian Conflict

This section describes an application of the nested network model (3.15) - (3.18) to the Israeli-Palestinian conflict. The purpose is to verify the model by analyzing the simulation results against the literature and real-life results. This is done by comparing the changes in positions of the agents and the final position agreement value of the coalitions. The simulation is analyzed for any of the three graphical results that indicate political instability, as explained in Section 4.2.

4.3.1 Motivation

The Israeli-Palestinian Conflict has many characteristics that make it a good case study. There exists a great deal of publicly available data. There have been prior attempts to model this conflict which are available for review and analysis, such as [24] and [5]. Two coalitions are well-defined and have integrity over the time window of interest. The conflict spans decades with frequent events. Despite these advantages, there are certain challenges involved in modeling the Israeli-Palestinian Conflict.

4.3.2 Unique Challenges

There are certain characteristics about the Israeli-Palestinian Conflict that are unique and make any modeling attempt difficult. Because the Holy Land contains populations and holy sites of Judaism, Christianity, and Islam, international conflicts are susceptible to strong, emotional opinions and events. The Israeli-Palestinian Conflict does not fit the conventional description of warfare, which is an outdated definition of action and response. [44] suggests that Israel, as a more western-style democracy, has weaknesses of dealing with borders, headquarters and conventional forces. Israeli dominance and Palestinian weakness in the conventional military arena encourages Palestinians to use asymmetric means to attack Israelis forces [32]. Therefore, a forecasting model should incorporate unconventional interactions, such as suicide bombing, a commonly-used tool since 1993.

While we apply the nested network model to the question of Palestinian nationhood, it is only one of many issues in the conflict (i.e. control over allotted lands, holy places, arable land, freedom of access, water resources, settlements, security, economic freedom, precise border demarcations, geopolitical strategy, quid pro quo, Jerusalem, legal status of Palestinian refugees, the Golan Heights, international recognition, and resource distribution). These other volatile issues are important, and it is likely that whenever peace accords occur, there will be consolidation and balance between them. By focusing on only one issue, we ignore the conflict's mixed nature, but create a tractable area of analysis.

4.3.3 Agent Subgroups

The simulation below is focused on the period from 1987 until the Oslo Accords in 1993. The subgroup agents are the Israeli Settlers, SHA, Hard-line Likud, Likud, Israeli Defense Forces, Labor Party, OCC, PEA, PLO, PFLP, and FND. These were determined by [5]. These agents are organized into two major coalitions: Israeli (Israeli Settlers, SHA, Hard-line Likud, Likud, Israeli Defense Forces, and Labor Party) and Palestinian (OCC, PEA, PLO, PFLP, and FND).

4.3.4 Parameter Table

Table 4.1 contains parameter value estimates for the agent subgroups for 1987. The close federation with Jordan represents a non-autonomous political entity that would be federated with Jordan. The parameter values for position, salience, and influence were obtained through Bueno de Mesquita' collaboration with Shmuel Eisenstadt and Harold Saunders as reported in [5]. We determined the firmness values by researching the profiles of each agent subgroup.

4.3.5 Model Verification

Figure 4.5 shows how the position values of the 11 agents evolve according to the dynamics presented in (3.15) - (3.18), with the first six agents in one coalition, the last five agents in another, and the following initial conditions:

$P[0] = \{100, 85, 85, 70, 60, 30, 25, 20, 20, 0, 0\}, \Phi_A[0] = \Phi_B = \{100, 85, 85, 60, 100, 60,$

$100, 70, 100, 20, 10\}, S[0] = \{99, 85, 90, 50, 80, 75, 95, 85, 95, 95, 80\}, F[0] = \{98, 97, 97,$

$96, 98, 96, 98, 97, 99, 96, 95\}, \epsilon = 10, \delta_1 = \delta_2 = .8, d = .0002,$ and $a = .00001.$

Agent	Influence	Position	Salience	Firmness
Israeli Settlers	100	100: Israel Annexes W.B and Gaza	99	98
SHA	85	85: 1987 Status Quo	85	97
Hard-line Likud	85	85: 1987 Status Quo	90	97
Likud	60	70: Palestinian territory with weakest autonomy	50	96
Israeli Defense Forces	100	60: Semi-autonomous Palestinian Territory	80	98
Labor Party	60	30: Close federation with Jordan	75	96
OCC	100	25: Close federation with Jordan	95	98
PEA	70	20: Loose federation with Jordan	85	97
PLO	100	20: Loose federation with Jordan	95	99
PFLP	20	0: Independent, secular, Palestinian State	95	96
FND	10	0: Independent, secular, Palestinian State	80	95

Table 4.1 Agent Parameters

The two coalitions reach position agreement values of 63 and 66. Although they do not exactly agree, these two coalitions have stable equilibrium position values that are close enough to suggest that they would agree to a negotiated settlement option. This value, which would represent a position somewhere between a semi-autonomous Palestinian Territory and one with weak autonomy, would match the result Bueno de Mesquita obtained. This simulated value also corresponds to the approximate position on Palestinian-nationhood agreed to in the 1993 Oslo Accords, where Peres and Arafat both became more moderate and the agents agreed to the establishment of the Palestinian National Authority, Israel's withdrawal from the West Bank and Gaza, and the eventual phasing-in of Palestinian self-government [5]. The negotiated agreements in Oslo in 1993 are interesting because the projected result from earlier analysis was closer to the 1987 status quo, a position near 85, but the actual result was much more in favor of the Palestinians [4].

This simulation is important because it displays two of the three graphical results that suggest political instability. First, a coalitional change could occur since the

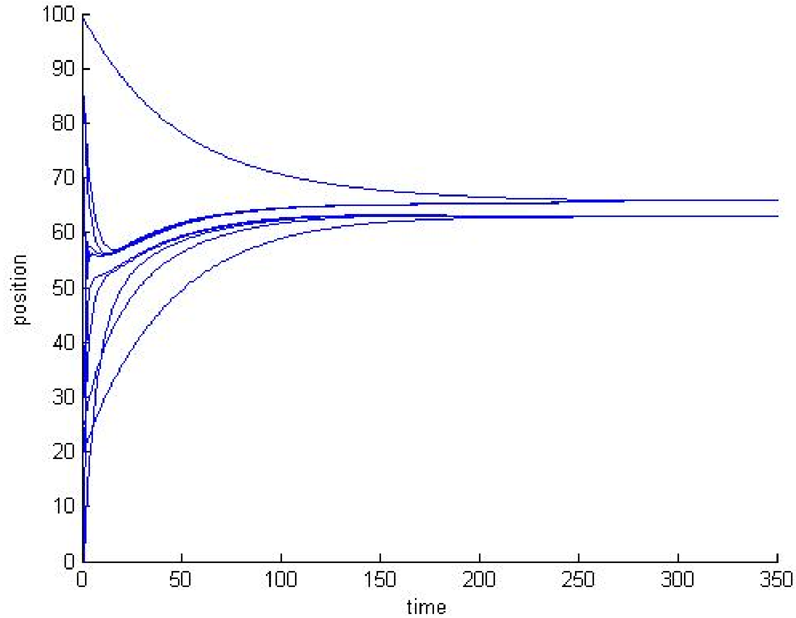

Figure 4.5 Nested Network Model Simulation

Israeli Settlers agent remains nearly 30 values above the rest of the Israeli coalition. As the most extreme agent in the coalition, they could be unsatisfied with the moderation of the other agents and consequently take some action. There is no significant bifurcation after attraction. The average weighted position begins at $\eta[0] = 61$, which matches the Likud-led Knesset of the time, but other agents quickly join its position and increase in their intracoalitional influence. No longer the sole agent at the average weighted position, there is an increased likelihood for the ruling party to be challenged. This simulated period of political instability matches the actual political instability that occurred in 1990.

The Israeli-Palestinian Conflict often leads to the end of political party agreements in the Knesset and the consequent dissolution of the Israeli government. In 1990, Yitzhak Shamir (Likud-PM) refused a peace initiative and a no-confidence motion ended the 23rd government of Israel. This is the only time to date that a government ended due to a no-confidence motion and it occurred during a time when Labor felt especially emboldened. Consequently, Peres (Alignment/Labor) was asked to try to form a government, and almost did so with Israeli Settler support, but eventually failed. The above simulation is interesting because it shows two things: a quick slide of Israeli agents from the upper extreme to the middle ground and the consequent loss of Likud having majority control over the average weighted position; and how the Israel Settlers were much more extreme than the rest of the Israeli agents and would have been dissatisfied with their moderate positions.

The Israeli agents' moderation and the Israeli Settler's continued extremism on the issue of Palestinian statehood would have been apparent had our model been applied in 1987. The simulation result would have been a forecast of political instability, which turned out to be the case with the no-confidence vote and attempt to form a new government described above.

Chapter 5

Conclusions

The model described in (3.15) - (3.18) appears to be useful for forecasting political instability because the simulated position agreement value matched the real-life value and because the simulation dynamics matched the lack of support for the Likud-led Knesset in 1990. We have explored an external data analysis method and found certain susceptibilities to error that directed us to focus on internal dynamics models. With the assumption that people change their positions on issues based on the assimilation of those around them, we used consensus model elements as our foundation. Finding our linear position dynamics (3.5) to be limited in their ability to simulate stable disagreement, we added nonlinear influence dynamics (Section 3.3.3) and a network hierarchical structure (Section 3.3.4) – thus allowing for different intracoalitional and intercoalitional influences as well as different levels of attention or trust between coalitions. Our findings suggest that an internal dynamics model (3.15) - (3.18) built from consensus model elements may be capable of forecasting political instability. We believe that although our nested coupled system is not the complete "Newton's Law" that needs to be understood in order to perfectly forecast political instability; nevertheless, the results are encouraging enough to suggest that consensus models are an appropriate tool for the problem.

5.1 Further Work

While this paper has summarized the two major modeling methodologies and presented our own variation of one of them, there are additional research ideas that can be explored. With region-specific adaptations, our model could be applied to other conflicts. Another variation would involve pairwise influence. Although this concept is partially addressed by using multiple δ's in (3.9), it could be done by creating a separate influence for each agent pair in the model. Adding dynamics for the salience and firmness of agents would be another interesting variation for our model.

Dual-state agents, where each agent has a true state and a declared state, would better reflect the real-life negotiation situation of the Israeli-Palestinian Conflict. It is likely that the declared position of an agent would be more aggressive, while its true position would be less so. In the West, this hidden position may be permanently obscured; however, in the Middle East, the true position could be revealed given enough time and a sufficient amount of leaked information.

A weighted arrangement where as each round proceeds, each agent places more weight on the true position and less weight on the declared position, could be constructed. By varying the weights and the number of rounds necessary until full disclosure, different simulations could be done.

An unresolved issue is whether influence is a zero-sum commodity. This depends on if an agent's influence is described as the share of influence or if an agent can increase in influence without another agent losing influence. In certain applications, it makes sense for influence to be some finite quantity that is shared; in others, it makes sense for an agent to be able to increase or decrease in influence without affecting other agents' influence. In this paper, we did not treat influence as a zero-sum commodity, but it would be interesting to see how such a change would affect the dynamics of the simulation.

We view this thesis as an attempt to summarize the two approaches to forecasting political instability and to present innovations on previous attempts. Encouraged by the results predicting the political instability in the Knesset in 1990, we plan on continuing to investigate this research area in future work.

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