Research Methods for Studying the Complexity Dynamics of Leadership

Kevin J. Dooley

Arizona State University

Benyamin Lichtenstein

University of Massachusetts Boston

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Kevin J. Dooley

Arizona State University

Benyamin Lichtenstein

University of Massachusetts

Contact information:

Kevin Dooley
Dept. of Supply Chain Management
W. P. Carey School of Business
PO Box 874706
Arizona State University
Tempe, AZ 85287-4706
Phone: 480-236-9588
Email: Kevin.Dooley@asu.edu

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Research Methods for Studying the Dynamics of Leadership

Abstract

Significantly novel leadership theory can be developed by examining the dynamics of leadership processes. Leadership dynamics are temporal patterns of leadership action and interaction which may impact group performance positively or negatively. Leadership dynamics can exist a multiple time scales—from minutes to hours to days to months. This chapter presents an integrated research methodology for studying leadership dynamics at three time scales: real-time observation for micro-scale dynamics, social network analysis for meso-scale dynamics, and event history analysis for macro-scale dynamics. Examples are presented from a case study, the ASU Software Factory, where the methodology was employed.

INTRODUCTION

In the new view of complexity leadership, leading is a process that can occur in the interactions between any two individuals (cite papers in this volume). In contrast to the old view of a single leader who takes independent actions aimed at changing individual- and organizational behavior, the new complexity leadership focuses on the dynamics of leadership as it emerges over time in all arenas of an organizational system. Each interchange and every connection provide opportunities for leading, as peers individually and collectively learn and grow and engage in the continuous process of organizing (Weick, Sutcliffe & Obstfeld, 2005; Uhl-Bein, in press).

Seeing leadership as a relational phenomenon that is distributed across individuals goes beyond current conceptions of shared leadership (Pearce & Conger, 2003), collective leadership (Weick & Roberts, 1993), distributed leadership (Gronn, 2002), or relational leadership (Drath, 2001; Uhl-Bien, in press). A new view recognizes the dynamic interplay of leading in organizations, attending to the way leadership emerges multiple levels and multiple time scales (Lichtenstein, et al., 2006b). Complexity leadership focuses on these processes of change in individuals, groups, ventures, organizations and institutions occurring in daily interactions, interventions that occur in weekly or monthly timescales, and macro-social events that accrue over months and years. Two good examples of emergent leadership at multiple levels are Chiles, Hench & Meyer's (2004) analysis of how entrepreneurial and institutional interactions led to the emergence and transformation of Branson, MO; and Plowman et al's (in press) exploration of multiple levels of activity that led to the continuous-radical transformation at "Mission Church."

Given the importance of understanding how leadership emerges through specific interchanges – differently in every interaction – we need to develop a methodology for identifying and in some way measuring these complex and temporally-based leadership dynamics. A variety of methods have been offered that might accomplish this task, but until now these approaches have not be categorized or brought together. For example, Dooley, Daneke, & Pathak (2005) have tracked the daily media interactions of Motorola's Iridium venture, showing how its failure was related to certain errors of leadership timing during start-up. Alternatively, social networks have been used to explore the interactions leading to long-term changes within a leadership context (e.g. Carley, Lee & Krackhardt, 2001; Schreiber, Singh & Carley, 2004). In contrast, an event history analysis approach was used by Lichtenstein and his colleagues (Lichtenstein, Dooley & Lumpkin, 2006) to explore the leadership activities of one entrepreneur who was trying to start-up a new business venture. The objective of chapter is to present an integrated research methodology which studies the dynamics of leadership interactions over time.

Leadership Dynamics as a Fractal Time Ecology

According to the recent research in complexity leadership, the essence of leading occurs in the interactions between individuals, interactions that by their nature are dynamic, i.e. they occur *in* time and *across* time(s). Time and temporal dynamics have been shown to have a critical effect in explaining emergence (Lichtenstein, Carter, Dooley & Gartner, in press) and the leadership of emergence (Plowman, in press). What we present is a broader framework that recognizes three differing scales of time – micro, meso, and macro – and how these interact to create what Koehler (2001) has termed a "fractal time ecology."

Leadership can occur in minute-by-minute interactions – the micro-level conversations and interactions of individuals working together in a focused way. Methodologically, such micro-level interactions can be shown to have a dynamical signature (Dooley & Van de Ven, 1999), representing an underlying pattern of order. This pattern can inform us of the underlying drivers of the process, which is a crucial component of what we are seeking in a complexity theory of leadership.

In addition, leadership occurs in interactions and outcomes at a meso-level, i.e. through daily and weekly small-scale changes in behaviors and relationships processes within an organization. Similarly, leadership can occur in macro-level time – over weeks and even months through significant events and emergent sense-making that can guide the cognitive and behavioral routines of individuals and whole organizations. Like interactions at a micro-level, an analysis meso-level and macro-level interactions and their outcomes may reveal patterns which help explain exactly how leadership emerged in those interactions, as well as other causal dynamics in the system.

In a fractal time ecology (Koehler, 2001) the assumption is that dynamical patterns at one level of interaction are linked to emergent patterns at other levels. For example, dynamical patterns at a micro-level time horizon may be linked to emergent patterns in meso- and macro-level time horizons. In the context of a group, we suggest that patterns of leadership interaction enacted minute-by-minute may be connected to the patterns observed over days, weeks, months, and years. In this way, the patterns are "fractal," since the same patterns may be repeated at multiple scales. For the same reasons, macro-patterns may constrain meso- and micro-patterns. These links between levels reflect an ecology of interactions, which is at the heart of an complexity model of leadership.

In this chapter we discuss specific research methods for studying leadership interaction at these three different time scales:

- ☑ Micro-scale interactions can be studied with Real-Time Observation techniques (Dooley et al., 2003);
- ☑ Meso-scale interactions across days and weeks can be studied using Social Network Analysis (Wasserman & Faust, 1994), and
- ☑ Macro-scale interactions across weeks, months and even longer can be studied using Event History Analysis (Poole, Van de Ven, Dooley, & Holmes, 2000)

Our goal is to provide examples of how these methods can be used to study leadership dynamics, and discuss practical implementation issues. However, the chapter is not meant to be a methods tutorial, nor do we attempt to develop specific theory from our analyses.

Studying leadership processes at multiple time-scales provides several benefits. First, comparison across time-scales allows us to study processes of emergence and structuration, which offer a much more in-depth view of the dynamics of leadership in interactions. Second, most existing leadership theories were developed outside of time, based on a cross-sectional view of leadership being directed from one person. A view of leadership that emerges in interactions requires a highly dynamic methodology which can capture the nuanced and multi-plex nature of those interactions and their results. These approaches, combining temporality and multiple levels, are likely to generate novel insights into leadership and its emergence throughout organizations.

Research Context: the Software Factory at ASU

As we explain each of the three methods, we will draw examples from a single context: the Arizona State University "Software Factory" (Dooley & Corman, 2002). The ASU Software Factory [SF] provided software development services to the research scientists within Arizona

State University (ASU). The development group was managed by a single professional manager, who oversaw six to eighteen employees (student programmers) at a time, organized into project teams of one to six people. Typical work projects involved re-engineering existing software code to extend functionality or translate to a new technology platform, and development of new software, primarily involving complex computation or equipment control.

The SF used "agile development methods" (Boehm & Turner, 2004) that included pair programming and frequent customer interaction. These methods reflect certain qualities that we see in complexity leadership, especially the phenomenon of leadership emergence (Guastello, 1995; Guastello, Hyde, & Odak, 1998). Specifically, aside from the single professional manager, there were no other defined roles, so any leadership network that emerged was due to the dynamic interaction of personalities and tasks. As the research methodology proposed in this paper was employed within the SF, we can speak directly to implementation issues. To our knowledge, the ASU SF represents the first setting in which all three of these time-scales were observed over years. Given this fact, and the qualities of leadership emergence within the SF, it is a useful and interesting context for us to draw on for this chapter.

STUDYING LEADERSHIP MICRO-DYNAMICS WITH REAL-TIME OBSERVATION

Many researchers believe that the best way to understand a human system is to directly observe it (Denzin & Lincoln, 2000). Real-time observation of human systems can occur in many ways, including through ethnography, field studies, conversation analysis, interaction analysis, discourse analysis, direct observation, high resolution broadband discourse analysis, etc (Dooley et al., 2003). The common thread amongst these different approaches is that communication and interaction amongst the agents in the system is observed in the smallest time-scale possible. Using Real-Time Observation (RTO) a researcher can begin to understand the micro-level thoughts and actions of organizational actors, and thus micro-level leadership interaction (Marion & Uhl-Bein, 2001). RTO enables cause and effect to be inferred between micro-level work patterns (e.g. patterns of communication during problem solving) and organizational performance (Senge, 1990). Within a leadership context, RTO can provide insight into how the group gains situational awareness, how it negotiates and coordinates action, and how social bonds that enhance trust and understanding are created or destroyed.

There are two challenges to RTO. First, collecting RTO data can be very time-consuming and expensive. If one wishes to capture all of the communication and interaction occurring within an organization, then one must have the means to "see" and "hear" everything that is going on. Traditionally, researchers have seen and heard via human observers. A "field researcher" attempts to observe and make sense of group behavior in real-time through note-taking, synthesis, and reflection. Aside from issues of bias and incompleteness, depending solely on human observers creates research logistics challenges; in order to capture micro-level behavior in a reliable way, one may need as many observers as there are participants, at which point we cannot assume the observation process itself is not impacting behavior. Human observers can be supplemented or even supplanted by technology (although humans still need to be involved in data interpretation). Due to advances in audio and video technology, researchers can capture a real-time record of group behavior and analyze it "off-line".

Even though technology can create efficiencies in observation of real-time behavior, the second challenge is that the volume of data generated is so large that it creates challenges in conversion (e.g. creating transcripts from audio tapes, or creating activity histories from video tapes), storage and retrieval, and analysis. Corman, Kuhn, McPhee, & Dooley (2002) estimated that approximately twenty thousand pages of transcripts are created from the conversations within a fifty person organization over one week of time. Until significant, additional breakthroughs occur in speech and video recognition, RTO will continue to be resource-intensive.

Within the ASU SF, three RTO methods were used. First, researchers did field observations within the facility. Because the facility was a single room, all workers could be seen from a single locale. Also, because conversation was not constant, it was possible to hear and take notes on what was being said between individuals. As much as possible, observers worked in pairs in order to increase reliability and interpretive capability. Second, a camera captured a picture of the facility every five minutes, and these pictures could be examined to see how people were configuring themselves in the facility, and how “socially active” the organization was at a given time.

Third – and most importantly for RTO – each participant wore a microphone for the entire period they were at work in the SF. When a worker came into the facility, they “checked in” at a PC which had software that (a) logged their name and time, and (b) created a identification stamp and a time stamp on their digital audio recorder, so exact (correct) times could be associated with the communication data on the recorder. At the end of the day, the worker would “check out” by hooking up the recorder to the PC which in turn would download all of the audio data to disk. Once a week a researcher then grabbed all of the audio files and uploaded them to a database which could be searched according to participant and day.

Logistics and Methods for Real Time Observation

Practically, we did not note any work-related problems with RTO of participants. All participants could request that certain taped data be erased (per human subjects agreement), but no requests were ever made. Participants were asked several times over the three years whether the recording equipment caused them to change their behavior, and the answer was always no; and field researchers never saw any evidence that RTO was generated a “Hawthorne” effect. Practically though, sustaining RTO was challenging. First, as time went on compliance by workers dropped off when the SF went from salaried to hourly employees. Second, there are many ways in which recorders can not do what they are supposed to—batteries can be dead, an off button can be pushed accidentally, microphones can break or not be plugged in. We found that a regular maintenance program, including reliability tests, was necessary to ensure good data. Third, while we captured almost all conversational data that occurred in the organization over a three year period, we did not realize ahead of time that much of the conversational data would be in Mandarin or Hindi rather than English. This in turn caused significant challenges with transcription.

We shall demonstrate the use of RTO with an example from part of a study examining pair programming (Boehm & Turner, 2004). Pair programming is a software engineering practice in which pairs program rather than individuals. The “driver” commands the keyboard and writes the software code while an “observer” watches for mistakes and generally helps out. Pair programming has been shown have a positive, significant impact on software code quality and programmer job satisfaction (Nosek, 1998). From a leadership perspective, we might be interested in how the pair manages its own work activities, and how it coordinates with other pairs.

In this example we used actual conversational data to understand the leadership dynamics within a project team. The team had been given a task which had two parallel subtasks, and the conversational data highlights how the group tackled those two tasks, and who was leading the coordination efforts. The conversational data was collected via microphones, as described above. Signal processing methods similar to those described by Choudhury (2004) were used on the raw audio streams in order to identify discrete conversational bits, and within each bit, who was talking to whom; the same data could have been generated by direct observation. Note that since there is no formal leader on the project, this methodological approach can provide unique insights into how leadership was enacted within and across each interaction of the pair.

RTO Data, Results and Analysis

Table 1 shows a portion of the data – the "bits" of conversations between the two pairs of programmers on this particular project. Each "bit" is indicated by a start time, a duration (in milliseconds), a speaker (S), and listener(s) (L). The two pairs were (M2 and M2) and (M3 and M4). Because concurrent conversations were captured, any conversation bit may have two, three, or four members.

Table 2 aggregates the data in Table 1 over two five-minute time segments. For example, the table indicates that between 13:20 and 13:25, M1 initiated interactions with M2 (their pair member) five times; however during this time period M2 is relatively silent, only listening to M1 (receiving). M1 also actively initiated interactions with the other pair members as well: M1 → M3 four times, and M1 → M4 three times. Again during this same five minute segment M3 and M4 primarily talk to themselves, they also – to a much lower degree – initiated with M1, who initiates and receives interactions with both of them significantly. Note that M2 initiates only two of the 35 initiations across the members (i.e. less than 6% of the total).

In the second five minute time segment these patterns change in an intriguing way. On the surface its clear that M2 becomes more involved in the interactions, tripling his level of initiated interactions from two to six. In addition, every member initiates at least one interaction with every other member, in contrast to the previous time segment in which three of the twelve possible initiations were unexpressed. At the same time, the total number of initiated interactions is virtually the same in both time periods: 37 in T1 vs. 38 in T2, indicating a similar lever of overall interaction. Moreover, the average number of initiated and received interactions is similar in both time periods – 8.8 in T1 vs. 9.5 in T2, indicating that the average level of interactions between members was not largely changed.

However, a deeper analysis suggests a significantly greater coherence of interaction across the group during the second time segment. Specifically, we compare the initiated interactions in T1 with the initiated interactions in T2, and similarly the received interactions in T1 with those in T2. In both cases the variance and the standard deviation of those interaction levels across the four members *drops* precipitously between T1 and T2. Specifically, the standard deviation of initiated interactions drops by 44% from T1 to T2, and the st.dev. of receptions drops by 56%. In other words, the second time period shows a much greater balance of interactions across all members, suggesting that they were working much more as a 4-person team than as two 2-person teams.

--INSERT TABLE 1—

--INSERT TABLE 2—

From a leadership standpoint, this difference at a micro-level may be the result of an aggregated shift in the leadership happening within each interaction (Lichtenstein et al., 2006b). At a meso-level the shift may be a response to some environmental influence such as a jolt, a punctuation, or an oscillation (Meyer, Gaba & Colwell, 2005). By studying these patterns over multiple work sessions, we can begin to understand whether these leadership patterns are persistent or contextual. It is worthwhile to note that we can make these inferences without direct examination of the content of their interactions; while co-referencing content would no doubt help validate or disconfirm these inferences, they emanate from a description of the dynamics only.

In summary, micro-level dynamics infer the action and communication patterns that characterize numerous behavioral constructs: (e.g.) problem solving, decision making, creativity, conflict, cooperation, and coordination. Techniques and methods associated with real-time observation provide a more process-oriented view of leadership than the more traditional view of leadership as personality or power. Instead, these models characterize leadership as a process of interaction.

STUDYING LEADERSHIP MESO-DYNAMICS WITH SOCIAL NETWORK ANALYSIS

Whereas real-time observation emphasizes observing reality, meso-level analysis emphasizes metric and perceptual data. In order to study dynamics at a meso-level (e.g. daily, weekly), a researcher can collect project, process, and performance data aggregated to whatever time frame is most useful for the context. In the SF we collected data such as hours worked per day, software changes made per week, customer contacts per week, etc. A researcher can also collect perceptual data from the participants through daily or weekly surveys or interviews. One particularly useful type of model for examining meso-level patterns of leadership is Social Network Analysis (Wasserman & Faust, 1994). Social Network Analysis [SNA] conceptualizes a social system as a set of nodes (agents) and connections between nodes. The structure of the social network, and the position of any particular agent's node, can be used to infer relational roles (Freeman, 1979). Most often, social networks are constructed based on individuals' perceptions of interaction, communication, or influencing. While SNA is well-established in social science, the study of dynamic networks is still developing (Snijders, 2001; Monge & Contractor, 2003).

From a leadership standpoint, SNA provides a relational model of leadership. Individuals with many connections, or connections that create boundary spanning, can be important in terms of enhancing social cohesion, facilitating information flow, and establishing cultural norms. Several leadership-related studies have SNA. For example, Balkundi & Kilduff (2006) explore how the network cognitions of leaders affect the pattern of interactions between themselves and other leaders in their networks. The social networks of group leaders have been shown to positively effect the group's performance and the leader's reputation (Mehra, Dixon, Brass & Robertson, 2006), as well as the perceived effectiveness of transformational leaders (Bono & Anderson, 2005).

Social Network Data and Analysis

Within the ASU SF, social network data was collected via a weekly survey which asked how often the respondent had communicated with all other employees and researchers. To smooth out the noise caused by missing data, we assumed that if one survey indicated communication with any person during the week, then the communication was bi-directional. From a practical standpoint, the only problem with collecting social network data was non-compliance with responding to the survey. This improved when we standardized the process of sending out the surveys and survey reminders. When confronted with missing data, we conferred with the official SF roster at that moment in time and if the person whose survey was missing was employed and not on leave, then the connections from the previous week's network were carried forward.

In this example, we are using SNA to examine how the SF's social network changed from week to week. By determining where change is greatest and relating that to known events, one can infer what type of events are likely to lead to change in social structure, and thus leadership patterns (Burkhart and Brass, 1990). A total of 62 weeks of social networks was captured and analyzed. In order to look for changes in communication and thus social structure, we calculated the correlation between each network using the QAP procedure (Wasserman & Faust, 1994). A graph of the correlation between two weeks' networks is shown in Figure 1. Low values of correlation (less than 0.30) correspond to significant changes in the social network structure, and thus the potential onset of (new) emergent leadership. In order to determine the reasons behind changes, we examined a timeline of SF-related events and were able to find tentative explanations for these changes.

--INSERT FIGURE 1--

We see that changes in social structure occur when significant personnel changes occur. Participant 6522 has an important influence when they join the organization in week 5; likewise, a number of new employees are hired around week 15, corresponding to the beginning of the Fall semester, and this leads to changes in structure. Participants 3311, 4599, and 3458 have an impact when they join and leave for the summer, and return after the summer (3311). It is important to note that over thirty individuals joined and left the organization during this time frame, so only a small fraction of participants had a significant impact on the social structure. By exploring more deeply we could identify to what degree this impact was due to that individual's leadership in interactions, which has been shown to increase the quality of their social network (Balkundi & Kilduff, 2006).

For example, examination of the individual networks indicates that 6522 was at the center of the SF's first clique, while 3311, 4599, and 3458 were important in creating social coherence and a sense of pride (and competition) amongst employees. These three were relatively extroverted compared to the rest of the employees, and had a greater desire for the quality of their work to be known and appreciated by others. Our argument is supported by the fact that two of these three received a coveted acknowledgement of their performance: they were the only SF employees that year to obtain a summer internship from Microsoft.

In summary, meso-level dynamics infer organizational routines, networks of communication and influence, leadership emergence amongst sets (or cliques) of individuals, and the influence of macro-level (institutional) dynamics such as planning or hiring cycles. Social network analysis creates a model of leadership that is relational and relative; an arrival or departure of a single individual can cause ripples in how leading is distributed within the group, and create opportunities for new leadership emergence. Here again we demonstrate a method based on process, without the usual focus on content. Certainly more in depth explanations could be developed for these network changes; our goal here is simply to show how temporally-based methods, even without much content, provide a unique view into the dynamics of leadership at ASU's Software Factory.

STUDYING LEADERSHIP MACRO-DYNAMICS WITH EVENT HISTORY ANALYSIS

When leadership interactions occur across multiple constituencies over time, focusing on each individual interaction or on specific interactions across network ties can lead to an overload of data without any basis for generating insight at a larger time-scale. Thus, a third approach to exploring the dynamics of leadership interactions uses the "event" as a unit of analysis (Abbott, 1992). More commonly called "event history analysis" (EHA), this method is designed to capture the aggregated leadership actions across multiple individuals, the emergence of which signals some substantive change in the nature of the system as a whole (Poole et al., 2000). That is, by defining an "event" as a macro-level emergent phenomenon which creates some long-term change in the system, a dynamic structure is created that integrates a vast amount of data over long periods of time (Van de Ven & Engleman, 2004). Further, by identifying key events over time, the evolution of leadership in the system can be readily explored (Chiles et al., 2004; Lichtenstein, et al., 2006).

EHA involves three steps: collection of event data, coding of event data, and analysis of event codes. EHA facilitates study of the leadership process to the extent that events are coded with respect to a construct or set of constructs that relates to a leadership theory-frame. Defining these constructs – agreeing on what "counts" as a significant leadership event – would be a critical aspect of this overall process. Several previous leadership studies have used EHA, including Chiles, et al, 2005.

Event History Data and Analysis

Within the SF, events were noted by the SF research and administration teams, who had constant oversight into SF operations. Events were defined and coded for four types of leadership: influential, transactional, strategic, or participatory leadership. Events were entered into a database, and at a later time several coding schemes were developed to examine different research questions. Table 3 shows a list of events as they occur on a day-to-day basis; here an X indicates that *at least* one event occurred in that time period. Table 4 shows the aggregated event counts per week.

--INSERT TABLE 3--

--INSERT TABLE 4—

EHA suggests different dynamics for different types of leadership amongst participants. Influence leadership in this case was aimed at developing strategic relationships with key internal research laboratories. Most of this was concentrated in the first month of operations; since the hiring cycle primarily operates on a semester to semester basis, we would expect this pattern to repeat in subsequent semesters. We also see that transactional leadership events occur more frequently in the beginning of the semester, indicative of the need to implement new processes and systems within the SF as a new semester commences. Strategic leadership events are spread uniformly throughout the time frame, indicating that strategic-level issues were considered as part of normal administrative overview. Participatory leadership also peaked in the first months; as work continued less attention was paid to improving the social structure until end of semester events were planned. Overall the results show that while strategic leadership was constant over the period, other forms of leadership diminished as work loads increased.

However, a deeper analysis again shows an intriguing macro-pattern – a change point within this semester-long period of data. We assume as before that leadership emerges through interactions, and we suggest that the four types of leadership we have coded here do represent a kind of leadership interaction. By adding all leadership events each week and presenting these in a graph, a very distinct pattern of leadership emerges (see Figure 2). Essentially the number of leadership events rises dramatically in the first six weeks of the semester, from 3 per week to 11 in week six; then they drop precipitously for the rest of the semester, to an average of 1.75 per week from the previous six-week average of 5 per week.

--INSERT FIGURE 2—

The size of this drop, coupled with the very distinct qualities before the change point and afterwards, suggests that a very different type of leadership is being enacted in these two phases of activity. In the first phase the sheer volume of leadership suggests that the system is out of balance, and requires a significant amount of internal leadership to bring it back into coherence. This process work appears to reach a critical threshold in week 6, after which the system appears to shift into a much more stable period, perhaps reflecting a sense of balance which allows the employees to focus much more on task behaviors rather than on group-maintenance behaviors.

Previous work using EHA has shown similar results (e.g. Lichtenstein et al., 2006a), suggesting that the nature and quality of leadership in interactions may shift over time. These shifts may indicate macro-level punctuated changes in the direction or orientation of the project, or they may reflect internal oscillations that are directed from the environment – in this case, the pattern of the semester. Either way, by comparing the events semester by semester, some intriguing insights may be gained in terms of how leadership is effected by these macro-level changes, and how it may be a cause of the macro-level patterns.

In summary, macro-level dynamics infer the roles that individuals play within the larger system, how the organization as a whole strategically adapts to changes in the environment, the impact of institutional events such as planning and hiring cycles, and how micro- and meso-level patterns (such as emergent leadership) impacts longer time-scale dynamics. EHA facilitates multiple theoretical perspectives be brought to bear on macro-level data, as each event can be coded in numerous ways, depending on the constructs being used relative to the research questions(s) at hand. EHA characterizes leadership as a path dependent sequence of events, and by examining how event tallies change over time, we can observe different types of macro-level patterns.

GOING THE NEXT STEP: INTERACTIONS BETWEEN TIME SCALES

As we have seen, studying leadership dynamics at different time scales will yield different insights. While each level can be examined independently, researchers should develop research plans which allow one to examine the co-occurring dynamics at all three levels. Only by understanding linkages across time scales can we paint a complete picture of how leadership emerges and evolves in a complex system.

In our case, and even with a minimal amount of analysis, a faint pattern may be discernable across the three time scales. At the micro level there was a clear distinction between the first and the second time segments. In the first segment, the interaction patterns showed a separation between the two teams, where M1 mostly initiated conversation with M2 (although M2 didn't much respond), whereas M3 and M4 had the majority of their interactions between themselves. In contrast the second time segment showed far more balance and in the interchanges between all four members; this concordance across interactions was reflected in the significantly decreased standard deviations of both initiations and receptions amongst all four participants.

At the meso-level we saw a pattern of significant shifts in the network's structure over time. These shifts reflected in part the large influence of a small number of key individuals who brought a great deal of coherence to the networks; this coherence was disrupted when they left (e.g. for the summer) and it returned on their re-entry. At the macro-level we again see a pattern of increased turbulence at the beginning, followed by a distinct change point that ushers in a period of relative coherence.

A deeper analysis would explore this pattern more carefully at all three levels. On the surface it appears to be fractal, i.e. the dynamics at the micro level seem to be repeating themselves at the meso-level, and again at the macro level. If so, we have evidence of a fractal time ecology, which helps us understand and support interactive leadership in a much more subtle and potentially effective way.

In general, two mechanisms explain potential linkages between micro-, meso-, and macro- time-scales. First, stable patterns of micro-activity may emerge due to endogenous and exogenous effects, which *entrain* these patterns across time-scales. That is, human agents choose archetypal patterns of interaction and then enact these patterns at different time-scales, leading to time invariant patterns across temporal levels. For example, a particular work group may tend to utilize an escalation dynamic as a means of organizing. At micro-temporal scales, this escalation dynamic may manifest itself as binges of creativity and/or escalating conflict during group discourse (Perry-Smith & Shalley, 2003), while at macro-temporal scales it may manifest itself as an escalating commitment of resources (Ross & Staw, 1993).

Second, macro-level patterns may *constrain* finer-grained patterns through establishing temporal boundaries and subsequent "windows of opportunity." In our example the cycle of the semester created a natural constraint on the meso- and macro-patterns within the SF, and perhaps on the micro-level interactions. In other ways, seasonal changes in work load or resource availability create natural, periodic forces that constrain the dynamics of micro-activities to be periodic also. If dynamic patterns of leading are similar across time-scales, then micro-level leadership behavior can be observed and used to predict what macro-level behavior and outcomes will emerge. This improves a group's ability to self-monitor its performance in (near) real-time and take corrective action as necessary. For example, if conversational patterns were shown to scale to long-term patterns of group member satisfaction, then groups could be trained in how to create positive conversation patterns and monitor for dysfunctional patterns.

If similarities across time scales are not directly observed, it may be because more complex linkages across levels are operating (Poole & Van de Ven, 2004). Lack of temporal scaling would suggest that the observed leadership process is a relatively "high dimensional" phenomenon, meaning that an organization's dynamics emerge from the interaction of a large number of factors (Dooley and Van de Ven, 2000). In such circumstances, the leadership process must be characterized as highly idiosyncratic and contextual. In any actual leadership process, we would expect to observe elements of both—along certain dimensions of leadership activity we may observe temporal scaling and strong, low-dimensional (simple) generative mechanisms, and along other dimensions we may observe more complex interactions indicative of high-dimensional behavior; such differences may be due to the degree of influence from factors exogenous to the leadership process.

CONCLUSION

Complexity Leadership is offering a new theoretical framework for explaining the how leadership is enacted within the interactions of all organizational members, rather than by a specific person through their interactions only (Marion & Uhl-Bein, 2001; Uhl-Bein, in press). This perspective may offer new insights into the emergence of innovation, the creation of order, and the dynamics of performance in 21st century networks and organizations (Lichtenstein et al., 2006b).

The potential value of this effort is matched by its unique demands, namely the need to examine *how* leadership is expressed in the "space between" individuals, i.e. in every day interactions (Bradbury & Lichtenstein, 2000). That is, in order to gain new insights into the dynamics of interaction we must go beyond – far beyond! – the traditional method of collecting data in one-time cross-sectional surveys. Specifically, capturing the subtle dynamics of leadership-within-interactions will require studies that are longitudinal and multi-level, collecting data that is rich and multi-faceted enough to capture the subtlety of the patterns in the system, and at the same time developing analyses which are abstract enough to see those patterns above the "trees" and branches and leaves and weeds of data (McKelvey, 2004; Lichtenstein et al., 2006a). This chapter provides one pallet of possibilities for collecting data and framing analyses with these goals in mind.

Equally, this effort emphasizes an important direction in the application of complexity to management, and that is the use of real (non-simulated) data from real (non-computational) organizations. This direction, which runs counter to currently accepted norms in the emerging field of complexity, reflects a value on the richness and diversity of every-day organizational life, over and above the more commonly taken path of doing in-depth theory-creating simulations that are based on an unrealistically simple model of human behavior. Although there is room for simulation-based theory development (McKelvey, 1997; 1999), the quality of leadership in interactions is subtle and tacit, making it difficult to generate accurate computational models that reflect the degree of richness and (literally) complexity in behavior that a complexity theory of leadership is seeking to uncover.

The good news is there are an increasing number of non-simulation-based exemplars of complexity, each of which provides insights into the methods that can be used to uncover patterns of leadership interaction over time (e.g. Guastello, 1995; Chiles et al., 2004; Lichtenstein, et al., 2006a; Plowman et al., in press). When combined with the right questions – many of which are represented in the papers that appear in the present volume – we will make strong headway in developing a new theory of leadership that goes beyond the myths of the hero or the scapegoat, and instead reflects that dynamic and emergent nature of leadership as it is enacted every day in some way by all members within and beyond organizations.

REFERENCES

Abbott, A., 1992. From causes to events: Notes on narrative positivism. ***Sociological Methods and Research.*** 20: 428-455.

Balkundi, P., & M. Kilduff, 2006. The ties that lead: A social network approach to leadership. Leadership Quarterly, 17: 419-439.

Boehm, B., R. Turner, R. 2004, *Balancing Agility and Discipline*, Boston: Addison Weseley.

Bono, J. & Anderson, M., 2005. The advice and influence networks of transformational leaders. *Journal of Applied Psychology*, 90: 1306-1314.

Bradbury, H., & B.M. Lichtenstein, 2000. Relationality in organizational research: Exploring the "space between." ***Organization Science,*** 11: 551-564.

Burkhardt, M. E., & Brass, D. J. (1990). Changing patterns of patterns of change: The effects of a change in technology on social network structure and power. Administrative Science Quarterly, 35(1), 104-127.

Carley, K. M., Lee, J. S., and D. Krackhardt (2001b), Destabilizing Networks. *Connections*, 24:3, 31-34.

Chiles, T., Meyer, A., and T. Hench (2004), Organizational Emergence: The Origin and Transformation of Branson, Missouri's Musical Theaters, *Organization Science*, 15, 499-520.

Choudhury, T. (2004), Sensing and Modeling Human Networks, Ph.D. Thesis, MIT.

Corman, S., Kuhn, T., McPhee, R., and K. Dooley (2002), "Studying complex discursive systems: Centering resonance analysis of organizational communication," *Human Communication Research*, 28(2): 157-206.

Denzin, N.K., & Lincoln, Y. S. (Eds.) (2000). Handbook of Qualitative Research. Thousand Oaks, CA: Sage.

Dooley, K., and S. Corman (2002), "Arizona State University's Software Factory," 2002 Decision Sciences Conference, San Diego.

Dooley, K., Corman, S., McPhee, R., and T. Kuhn (2003), "Modeling high-resolution broadband discourse in complex adaptive systems," Nonlinear Dynamics, Psychology, & Life Sciences, 7(1): 61-86.

Dooley, K., Daneke, G., and Pathak, S. (2005), "Iridium's house of cards: The nature of entrepreneurial stages and stage transitions," Academy of Management Conference, Aug 5, 2005, Honolulu.

Dooley, K. & Van de Ven, A., 1999. Explaining complex organizational dynamics. *Organization Science,* 10: 358-372.

Drath, W. (2001), *The Deep Blue Sea: Rethinking the Source of Leadership*, San Francisco: Jossey-Bass & Center for Creative Leadership.

Freeman, L. C. (1979). Centrality in social networks: Conceptual clarification. Social Networks, 1, 215-239.

Guastello, S.J. (1995), "Facilitative Style, Individual Innovation, and Emergent Leadership in Problem Solving Groups," ***Journal of Creative Behavior,*** 29(4):225-39.

Guastello, S.J., Hyde, T., and Odak, M. (1998), "Symbolic Dynamic Patterns of Verbal Exchange in a Creative Problem Solving Group," ***Nonlinear Dynamics, Psychology, and Life Sciences,*** 2(1):1 35-58.

Gronn, P. (2002), Distributed Leadership as a Unit of Analysis, ***Leadership Quarterly,*** 13: 423-451.

Koehler, _ 2001. ?

Lichtenstein, B., N. Carter, K. Dooley & B. Gartner, in press. Complexity dynamics of nascent entrepreneurship. ***Journal of Business Venturing.***

Lichtenstein, B., Dooley, K., & Lumpkin, T. 2006a. Measuring emergence in the dynamics of new venture creation. ***Journal of Business Venturing,*** 21: 153-175

Lichtenstein, B., M. Uhl-Bein, R. Marion, A. Seers, J.D. Orton, and C. Schreiber, 2006b. Complexity Leadership Theory: An interactive perspective on leading in complex adaptive systems. ***Emergence: Complexity and Organization.***

Marion, R., and M. Uhl-Bien (2001), Leadership in Complex Organizations, ***Leadership Quarterly,*** 12, 389-418.

McKelvey, B. 1997. Quasi-natural organization science. ***Organization Science,*** 8: 351–381.

McKelvey, B., 1999. Toward a campbellian realist organization science. In J. Baum & B. McKelvey (Eds.) ***Variations in Organization Science.*** Thousand Oaks, CA: SAGE.

McKelvey, B., 2004. Toward a complexity science of entrepreneurship. ***Journal of Business Venturing,*** 19: 313-342.

Mehra, A., Dixon, A. Brass, D., & Robertson, B., 2006. The social network ties of group leaders: Implications for group performance and leader reputation. ***Organization Science,*** 17: 64-79.

Monge, P. R., & Contractor, N. (2003). ***Theories of Communication Networks***. New York: Oxford University Press.

Nosek, J. (1998), “The case for collaborative programming,” ***Communications of the ACM,*** March: 105-108.

Pearce, C. L., and J. A. Conger (2003), ***Shared Leadership: Reframing the Hows and Whys of Leadership,*** Thousand Oaks: Sage.

Perry-Smith, J. & Shalley, C., 2003. The social side of creativity: A static and dynamic social network perspective. ***Academy of Management Review,*** 28: 89-106.

Plowman, D.E., L Baker, T. Beck, M. Kulkarni, S. Solanksy, and D. Travis, (in press). Radical change accidentally: The emergence and amplification of small change. ***Academy of Management Journal,*** in press.

Plowman, D.E., (in press). The role of leadership in the emergence of order. ***Leadership Quarterly.***

Poole, M., Van de Ven, A., Dooley, K., and M Holmes (2000), ***Organizational Change and Innovation Processes: Theory and Methods for Research,*** Oxford: Oxford Press.

Ross, J. & Staw, B., 1993. Organizational escalation and exit: Lessons from the Shoreham nuclear power plant. ***Academy of Management Journal***, 36: 701-732.

Schreiber, C., Singh, S., and K. M. Carley (2004c), *Construct: A Multi-Agent Network Model for the Co-Evolution of Agents and Socio-Cultural Environments*, Carnegie Mellon University, Institute for Software Research, International. Technical Report, CMU-ISRI-04-109.

Senge, P., 1990. ***The Fifth Discipline.*** N.Y.: Doubleday.

Snijders, T. A. B. (2001). The statistical evaluation of social network dynamics. ***Sociological Methodology*** 2001, Vol 31: 361.

Uhl-Bien, M. (In press). Relational leadership theory: Exploring the social processes of leadership and organizing. ***The 2006 Yearly Review of The Leadership Quarterly***.

Van de Ven., A. and R. Engleman, 2004. Event- and outcome-driven explanations of entrepreneurship. ***Journal of Business Venturing,*** 19: 343-358.

Wasserman, S., & Faust, K. (1994). ***Social network analysis: Methods and applications.*** New York: Cambridge University Press.

Weick, K. E., and K. H. Roberts (1993), Collective Mind in Organizations: Heedful Interrelating on Flight Decks, ***Administrative Science Quarterly,*** 38:3, 357-381.

Weick, K.E., K. Sutcliffe & D. Obstfeld, 2005. Organizing and the process of sensemaking. ***Organization Science***, 16: 409-421.

Table 1 Raw data showing conversation bits

start time	duration	1111	2222	3333	4444
13:15:34	8112	S		L	
13:16:18	4500	S		L	L
13:16:26	6330	L		L	S
13:16:31	6797			L	S
13:16:37	5979	L		S	L
13:16:42	5760			S	L
13:16:54	11539	S			L
13:16:57	11206			S	L
13:17:02	11139	S	L		
13:17:07	9975	S	L		
13:17:17	11606	S	L	L	L
13:17:22	5996			S	L
13:17:29	10180		S		L
13:17:29	5905	S	L		
13:17:43	5699			L	S
13:17:50	9879	L	S		
13:17:55	5651			L	S
13:18:00	8966	S		L	
13:18:07	6743	L		S	
13:18:13	5905			S	L
13:18:18	6271	S		L	
	S = Speaker				
	L = Listener				

TABLE 2 – ANALYSIS OF INTERACTION BITS

T1 - 13:20 to 13:25

TO -->	M1	M2	M3	M4	INITIATED
M1		5	4	3	12
M2	1		0	1	2
M3	3	0		9	12
M4	2	0	7		9
RECEIVED	6	5	11	13	

T2 - 13:25 to 13:30

TO -->	M1	M2	M3	M4	INITIATED
M1		3	4	5	12
M2	3		2	1	6
M3	2	1		6	9
M4	5	3	3		11
RECEIVED	10	7	10	11	

	M1	M2	M3	M4	AVERAGE	VARIANCE	ST.DEV.
INITIATED T1	12	2	12	9	8.8	22.3	4.7
INITIATED T2	12	6	9	11	9.5	7.0	2.6
RECEIVED T1	6	5	11	13	8.8	14.9	3.9
RECEIVED T2	10	7	10	11	9.5	3.0	1.7
COMBINED T1	18	7	23	23	17.8	56.9	7.5
COMBINED T2	22	13	19	22	19.0	18.0	4.2

Table 3 Event codes for event history analysis (portion)

Event Date	Influ.	Transc.	Strat.	Partic.
8/23/2002		X		
8/26/2002				X
8/27/2002		X		
9/4/2002		X		
9/5/2002			X	X
9/9/2002				X
9/10/2002	X			
9/11/2002		X		
9/12/2002		X		
9/16/2002			X	
9/16/2002		X		
9/18/2002		X		
9/18/2002		X		
9/20/2002		X		X
9/23/2002			X	
9/26/2002		X		
9/27/2002		X		X
9/30/2002				X
9/30/2002	X			
9/30/2002				X
9/30/2002	X			
9/30/2002		X		

Table 4: Week by week event counts for Event History Analysis.

	Influence	Transactional	Strategic	Participatory	TOTAL
8/26/02	0	2	0	1	3
9/2/02	0	2	1	1	4
9/9/02	1	1	0	1	3
9/16/02	0	4	1	1	6
9/23/02	0	1	1	1	3
9/30/02	3	5	1	2	11
10/7/02	0	0	1	0	1
10/14/02	0	1	0	0	1
10/21/02	0	1	2	0	3
10/28/02	0	0	0	0	0
11/4/02	0	2	1	1	4
11/11/02	0	0	1	0	1
11/19/02	0	1	0	0	1
11/25/02	0	0	1	0	1
12/2/02	0	1	0	0	1
12/9/02	1	1	0	1	3
12/16/02	0	1	2	1	4
12/23/02	0	1	0	0	1
TOTAL:	5	24	12	10	

Figure 1 Correlation between successive social networks

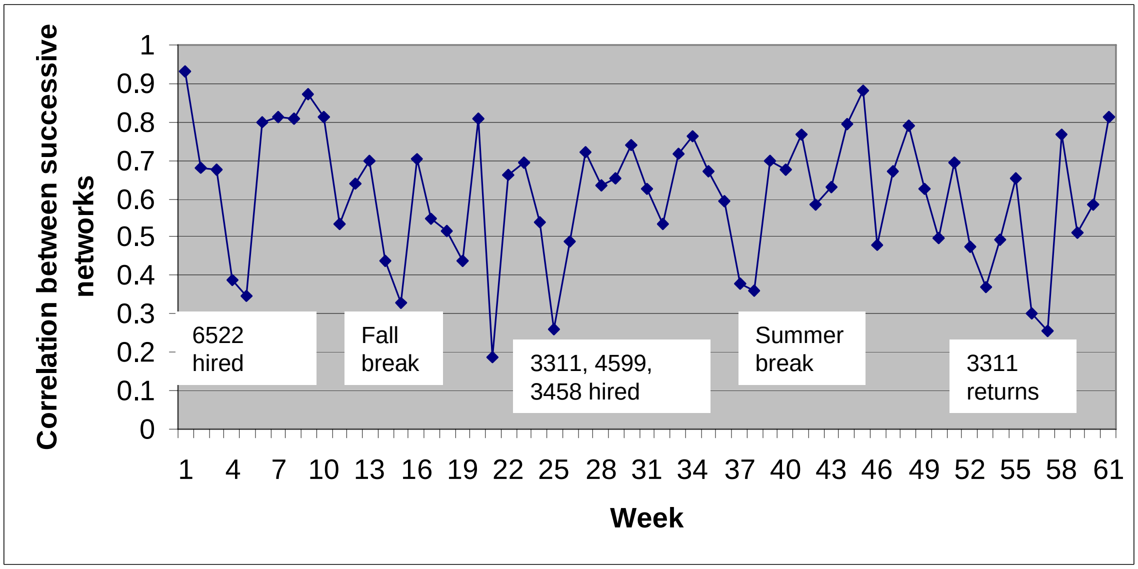

Figure 2: Changes in Leadership Events during 18-week period