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CHAOS THEORY AND STRATEGY: THEORY, APPLICATION, AND MANAGERIAL IMPLICATIONS

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This paper argues that chaos theory provides a useful theorectical framework for understanding the dynamic evolution of industries and the complex interactions among industry actors. It is argued that industries can be conceptualized and modeled as complex, dynamic systems, which exhibit both unpredictability and underlying order. The relevance of chaos theory for strategy is discussed, and a number of managerial implications are suggested. To illustrate the application of chaos theory, a simulation model is presented that depicts the interactions between a manufacturer of computers, its suppliers, and its market. The results of the simulation demonstrate how managers might underestimate the costs of international production. The paper concludes that, by understanding industries as complex systems, managers can improve decision making and search for innovative solutions.

INTRODUCTION

One of the enduring problems facing the field of strategic managment is the lack of theoretical tools available to describe and predict the behavior of firms and industries. For example, even if we know that oligopolistic industries are likely to experience periods of stability alternating with periods of intense competition, we do not know when they will occur or what will be the outcome. Similarly, it is almost impossible to predict the impact of the advent of a new competitor or technology in an industry. The fundamental problem is that industries evolve in a dynamic way over time as a result of complex interactions among firms, government, labor, consumers, financial institutions, and other elements of the environment. Not only does industry structure influence firm behavior, but firm behavior in turn can alter the structure of an industry and the contours of competition. Existing theoretical models, however, tend to assume relatively simple linear relationships without feedback. Indeed, many strategic theories attempt to classify firms and industries and to describe appropriate strategies for each class; examples include the Boston Consulting Group matrix for resource allocation and Bartlett's classification of international strategies (Bartlett and Ghoshal, 1989). Although these models are based on recurrent patterns that we recognize in the real world, there are usually far too many exceptions for the models to have much predictive value.

Chaos theory, which is the study of nonlinear dynamic systems, promises to be a useful conceptual framework that reconciles the essential unpredictability of industries with the emergence of distinctive patterns(Cartwright, 1991). Although chaos theory was originally developed in the context of the physical sciences, Radzicki (1990) and Butler (1990) amongst others have

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noted that social, ecological, and economic systems also tend to be characterized by nonlinear relationships and complex interactions that evolve dynamically over time. This recognition has led to a surge of interest in applying chaos theory to a number of fields, including ecology (Kauffman, 1991), medicine (Goldberger, Rigney and West, 1990) international relations (Mayer-Kress and Grossman, 1989), and economics (Baumol and Benhabib, 1989; Kelsey, 1988).[1] Despite the apparent applicability of chaos theory to the field of business strategy, there has been surprisingly little work in this area.

This paper introduces readers to chaos theory, and discusses its relevance to the social sciences in general and to aspects of strategy in particular, including planning and forecasting, and the impact of change on firms and industries. The application of chaos theory to a business situation is illustrated using a simulation model of an international supply chain. The model, which is based on the author's research into the supply chain of a California-based computer company, depicts the complex interactions between the firm, its suppliers, and its markets. The simulation results illustrate the managerial implications of applying chaos theory to strategic management. The model demonstrates how small disruptions to the supply chain interact to make the chain highly volatile, imposing significant costs on the organization. Although forecasting is very difficult in the supply chain, distinct patterns emerge which are useful for managers. The simulation also shows that by understanding the supply chain as a complex dynamic system, it is possible to identify managerial approaches that lower the cost of operating the supply chain.

AN INTRODUCTION TO CHAOS THEORY

Chaos theory is the study of complex, nonlinear, dynamic systems. The field was pioneered by Lorenz (1963), who was studying the dynamics of turbulent flow in fluids. Although we all recognize the swirls and vortices that characterize turbulent flow, the complexities of turbulent flow have confounded mathematicians for years. A similar problem afflicts someone who is trying to calculate the path of an object in the gravitational pull of two or more bodies. While we can use simple Newtonian equations to predict the orbits of planets around the sun with a high degree of accuracy, the mathematics involved in the case of two or more 'suns' become intractable. The problem can be illustrated on a terrestrial level by observing the motion of a simple toy, a metal ball suspended over two or more magnets. The ball will trace a series of patterns that never exactly repeat themselves, and yet are not totally random.

The paradox here is that the motion of the metal ball is driven by the same Newtonian equations as the well understood case of a single gravitational attractor. If we knew precisely the original location, speed, and direction of the ball, we ought to be able to predict its path with a reasonable degree of accuracy. How is it that deterministic systems can give rise to unpredictability? The explanation is that tiny variations in the motion of the ball are magnified every time it swings by one of the magnets. It is a combination of this divergence and the repeated interactions that give rise to 'chaotic' behavior. Mathematically, chaotic systems are represented by differential equations that cannot be solved, so that we are unable to calculate the state of the system at a specific future time 't'.

At the limit, chaotic systems can become truly random. A toss of a coin or the roll of a die are, in theory, deterministic systems, but yield more or less random outcomes. Not only is it impossible to toss a coin twice in exactly the same way, but on each toss the coin is subject to slightly different air currents, themselves a result of turbulent air flow (Ford, 1983).

To overcome the problem of intractable differential equations, researchers usually model systems as discrete difference equations, which specify what the state of the system will be at time 't+1' given the state of the system at time 't.' Computer simulations can then be used to see how the system evolves over time.

One of the major achievements of chaos theory is its ability to demonstrate how a simple set of deterministic relationships can produce patterned yet unpredictable outcomes. Chaotic systems never return to the same exact state, yet the outcomes are bounded and create patterns that

[1] See also special issues of *Journal of Economic Theory*, **40**(1), 1986, and *Journal of Economic Behavior and Organization*, **8**(3), 1987.

embody mathematical constants (Feigenbaum, 1983). It is the promise of finding a fundamental order and structure behind complex events that probably explains the great interest chaos theory has generated in so many fields.

Chaos theory and the social sciences

Proponents of chaos theory enthusiastically see signs of it everywhere, pointing to the ubiquity of complex, dynamic systems in the social world and the resemblance between patterns generated by simulated nonlinear systems and real time series of stock exchange or commodity prices. From a theoretical perspective, chaos theory is congruous with the postmodern paradigm, which questions deterministic positivism as it acknowledges the complexity and diversity of experience. While postmodernism has had a profound influence on many areas of social science and the humanities, it has been neglected by organization theorists until very recently (Hassard and Parker, 1993).

Despite its attractions, the application of chaos theory to the social sciences is still in its infancy, and there are those who think that expectations are too high (Baumol and Benhabib, 1989). Although real life phenomena may resemble the patterns generated by simple nonlinear systems, that does not mean that we can easily model and forecast these phenomena; it is almost impossible to take a set of data and determine the system of relationships that generates it (Butler, 1990). In fact, there is considerable debate in the economics and finance literature about how one tests a data series to determine if it is chaotic or simply subject to random influences (Brock and Malliaris, 1989; Hsieh, 1991). Moreover, it is important to recognize that many systems are not chaotic, and that systems can transition between chaotic and nonchaotic states. Chaos theory is perhaps better seen as an extension of systems theory (Katz and Kahn, 1966; Thompson, 1967) into the realm of nonlinear dynamics rather than as a total paradigm shift.

It is possible that the application of chaos theory to social science has been constrained by the fact that it has developed in relation to physical systems, without taking into account fundamental differences between physical and social science. In the social world, outcomes often reflect very complex underlying relationships that include the interaction of several potentially chaotic systems; crop prices, for example, are influenced by the interaction of economic and weather systems. The search for a simple set of equations to explain complex phenomena may be a futile attempt to construct grand 'meta-theory,' a project that is rejected in the postmodern paradigm. The application presented here uses a different approach; field study research is used to derive a set of relationships among variables and the influence of external systems is modeled probabilistically, a method suggested by Kelsey (1988).

Social and physical systems also differ in the source of unpredictability. In the physical world, unpredictability arises due to many iterations, nonlinearity, and our inability to define starting conditions with infinite precision. In the social world, far less accuracy is possible in defining starting conditions, and the specification of the system structure itself is much less precise.

A final difference is that physical systems are shaped by unchanging natural laws, whereas social systems are subject to intervention by individuals and organizations. Investigations of economic time series by chaos theorists have usually assumed that relationships among economic actors are fixed over time. In reality, methods of stabilizing the economy have changed from the use of the gold standard and balanced budgets to Keynesian demand management and, later, to monetarist contols. Human agency can alter the parameters and very structures of social systems, and it is perhaps unrealistically ambitious to think that the effects of such intervention can be endogenized in chaotic models.[2] Nevertheless, chaotic models can be used to suggest ways that people might intervene to achieve certain goals. The application presented here, for example, shows how management can reduce the volatility of the supply chain to improve performance.

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[2] To some extent, the distinction between endogenous and exogenous variables in a model is one of convenience; a factor that is exogenous in a simple model might become endogenous in a more complex and comprehensive one. Exogenous factors can be included as random variables in chaotic systems for modeling purposes (Kelsey, 1988).

RELEVANCE OF CHAOS THEORY TO STRATEGY

To understand the relevance of chaos theory to strategy, we need to conceptualize industries as complex, dynamic, nonlinear systems. Firms interact with each other and with other actors in their environment, such as consumers, labor, the government, and financial institutions. These interactions are strategic in the sense that decisions by one actor take into account anticipated reactions by others, and thus reflect a recognition of interdependence. Although interfirm behavior has been modeled formally in economics and business strategy using game theory (Camerer, 1991), these models tend to presume the emergence of equilibrium and do not adequately reflect industry dynamics. As Porter (1990) emphasizes, the evolution of industries is dynamic and path dependent: corporate (and country-level) capabilities acquired during previous competitive episodes shape the context for future competitive battles. Moreover, the accumulation of competitive advantage can be self-reinforcing, suggesting at least one way in which industries are nonlinear. If industries do behave as chaotic systems, a number of implications for strategy can be drawn.

Long-term planning is very difficult

In chaotic systems, small disturbances multiply over time because of nonlinear relationships and the dynamic, repetitive nature of chaotic systems. As a result, such systems are extremely sensitive to initial conditions, which makes forecasting very difficult. This is a problem that has confronted meteorologists trying to model the weather: the fundamental problem is trying to use finite measurements in an infinite world. A related problem is that as systems evolve dynamically, they are subject to myriad small random (or perhas chaotic) influences that cannot be incorporated into the model.

Formulating a long-term plan is clearly a key strategic task facing any organization. People involved in planning, whether in business, economics, or some other area, have always known that models are always just models, that forecasts are uncertain, and that uncertainty grows over time. Nevertheless, our conventional understanding of linear models and the influence of random errors would lead us to think that better models and a more accurate specification of starting conditions would yield better forecasts, useful for perhaps months if not years into the future. Chaos theory suggests otherwise; the payoff in terms of better forecasts of building more complex and more accurate models may be small. Similarly, we cannot learn too much about the future by studying the past: if history is the sum of complex and nonlinear interactions among people and nations, then history does not repeat itself. Concerning urban planning, Cartwright (1991) has noted that we have to acknowledge that 'a complete understanding of some of the things we plan may be beyond all possibility.'

The notion that long-term planning for chaotic systems is not only difficult but essentially impossible has profound implications for organizations trying to set strategy based on their anticipation of the future. Rather than expend large amounts of resources on forecasting, strategic planning needs to take into account a number of possible scenarios. Moreover, too narrow a focus on a firm's core products and markets might reduce the ability of the organization to adapt and be flexible in the face of change. The proliferation of joint-ventures and the acquisition by large firms of stakes in entrepreneurial enterprises can perhaps be understood as attempts to keep a foothold in a number of potential scenarios in the face of uncertainty and accelerating change.

Industries do not reach a stable equilibrium

The traditional approach to understanding the influence of industry structure on firm behavior and competitive outcomes has been derived from microeconomics, with its emphasis on comparative statics and equilibrium. More recent applications of game theory have attempted to account for interactions among small numbers of firms (usually two), yielding predictions about, for example, investments in R&D or plant capacity to seize first-mover advantages. Even the most complex game theoretic models, however, are only considered useful if they predict an equilibrium outcome. By contrast, chaotic systems do not reach a stable equilibrium; indeed, they can never pass through the same exact state more than once. If they did, they would cycle endlessly through the same path because they are driven by deterministic relationships. The implication is that industries do not 'settle down' and any apparent stability, for example in pricing or investment patterns, is likely to be short lived.

Chaos theory also suggests that changes in industry structures can be endogenous. Corporate decisions to enter or exit the market, or to develop new technologies, alter the very structure of the industry, which in turn influences future firm behavior. One of the most provocative and controversial elements of chaos theory is that chaotic systems can spontaneously self-organize into more complex structures (Allen, 1988). The notion has been applied to biological evolution (Laszlo, 1987) as well as to economic systems (Mosekilde and Rasmussen, 1986). In the context of business strategy, the concept could potentially be applied to the evolution of complex organizational relationships such as long-term contracts and technical cooperation with suppliers, and hybrid forms of organizational control such as joint ventures. Chaos theory suggests that new, more complex organizational forms will appear more frequently than if they were simply the result of random mutations.

Dramatic change can occur unexpectedly

Traditional paradigms of economics and strategy, which are generally based upon assumptions of linear relationships and the use of comparative static analysis, lead to the conclusion that small changes in parameters should lead to correspondingly small changes in the equilibrium outcome. Chaos theory forces us to reconsider this conclusion. Large fluctuations can be generated internally by deterministic chaotic systems. Models of population growth based on the logistic difference equation illustrate how sudden, large changes in population levels can arise from the dynamics of the system rather than from the influence of external shocks (Radzicki, 1990).[3] Similarly, if economic systems are chaotic then we do not need to search for wars or natural disasters to account for economic depressions or a crash in the stock market.

The size of fluctuations from one period to the next in chaotic systems have a characteristic probability distribution (Bak and Chen, 1991). Under this distribution, large fluctuations occur more frequently than under the normal distribution, suggesting that managers might underestimate the potential for large changes in industry conditions or competitors' behavior.

Small exogenous disturbances to chaotic systems can also cause unexpectedly large changes. The implication for business strategy is that the entry of one new competitor or the development of a seemingly minor technology can have a substantial impact on competition in an industry. An example that comes to mind is the way Dell's mail order strategy in the personal computer industry forced other companies to reduce their prices and reexamine their traditional high-cost sales and service channels.

Short-term forecasts and predictions of patterns can be made

Although the unpredictability and instability of chaotic systems has been emphasized, there is also a surprising degree of order in chaotic systems. Short-term forecasting is possible because in a deterministic system, given the conditions at time 't,' we can calculate the conditions at time 't+1.' A carefully constructed simulation model of a complex system with accurately specified starting conditions can yield useful forecasts at least for several time periods. Weather forecasts based on sophisticated computer models using measurements from thousands of points around the globe do provide useful forecasts for a few days, which is usually sufficient for purposes such as hurricane warnings. If we imagine that strategic decisions in companies are made on a monthly or even annual cycle, then industry simulation models might be able to make useful predictions over a time horizon of several months or possibly years.

Another feature of chaotic systems that lends them a degree of order is that they are bounded; outcome variables such pricing or investments in new capacity fluctuate within certain bounds that are determined by the structure of the system and its parameters but not its initial conditions. In the context of busines strategy these bounds

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[3] The logistic difference equation has the form: $P_{t+1} = P_t * R* (1-P_t)$
P, a fraction between 0 and 1, represents the population level as a proportion of the maximum carrying capacity of the environment. R is the growth rate from one cycle to the next. Population growth is constrained by the factor $1-P_t$, which can be understood as a resource constraint.

might be set by feedback loops such as the entrance of new firms or antitrust action by the government in response to monopolistic conditions.

Although we cannot forecast the precise state of a chaotic system in the longer term, chaotic systems trace repetitive patterns which often provide useful information. According to Radzicki (1990), deterministic chaos 'is characterized by self-sustained oscillations whose period and amplitude are nonrepetitive and unpredictable, yet generated by a system devoid of randomness.' For example, while we do not know exactly where or when tornadoes and hurricanes will strike, we do know what conditions lead to their occurrence, when and where they are most frequent, and their likely paths. In a similar way, we know that oligopolistic industries tend to alternate between periods of intense competition and periods of more cooperative behavior, though we do not know when an industry will make the transition from one state to another. To give a third example, we know that the economy cycles through recessions and booms, though we cannot predict very well the depth or duration of a particular recession (Butler, 199). Observing patterns is especially useful if we can associate different phases of the system with other characteristics; for example, there is a strong relationship between business cycles and other variables such as demand, interest rates, the availability of credit, vendor lead times, and the tightness of the labor market.

An intriguing aspect of the patterns traced by chaotic systems is that they are independent of scale; in other words, similar patterns are traced by a system whatever horizon is used to view it. Economic time series often appear to display this property. Stock prices, for example, display a remarkably similar pattern whether one observes daily changes over 1 year or minute-by-minute changes over a day. These images of patterns within patterns are termed fractals when they are generated by chaotic systems. In the natural world, fractals can be found in many phenomena, from the shape of coastlines to ice crystals. The implications for business strategy are not entirely clear. One interpretation is that previous experiences in an industry are likely to recur on a much larger scale. A second interpretation is that similar patterns of behavior might be expected whether one examines competition between countries, between firms in an industry, or even between departments in a firm.

Guidelines are needed to cope with complexity and uncertainty

'Strategy' can refer to a set of guidelines that influence decisions and behavior. It is the complexity of strategic interactions, whether in chess, soccer, or in business, that makes it essential to adopt simplifying strategies to guide decisions; even the most powerful computers are unable to track all possible moves and countermoves in a chess game. General Electric's well known strategy of being number one or number two in every industry in which it participates is a simple example of a guideline which may be generally useful but is not always optimal in every situation. We need general guidelines because it is impossible to specify the optimal course of action for every possible scenario.

It is important to distinguish the guidelines and patterns of behavior that constitute strategy from the underlying rules of the game. In a game of chess, for example, knowing the rules for playing the game does not necessarily give one insights into strategies for successful play. One can only learn these strategies after experiencing the complexities of interactions on the chess board. Indeed, because of the complexity of strategic interactions, one does not always know why a particular strategy is successful.

While the complexity of industry systems dictates the need for broad strategies, the dynamic nature of chaotic systems mandates that strategies adapt. As industry structures evolve and competitors change their strategies, a firm clearly needs to change its own guidelines and decision rules. The problem here is that there is no simple way of deriving optimal strategies for a given system. Indeed, in a complex system the best strategies might achieve goals indirectly and even appear counter-intuitive. The best way to improve quality is not necessarily to check every product several times: it may be to improve labor relations and thus gain labor's cooperation in finding ways to reduce defects. IBM's decision in 1981 to let other 'clone' manufacturers use the DOS operating system for personal computers helped competitors but also indirectly helped IBM to build market share by creating the industry standard.

In order to understand indirect or counter-intuitive means to an end, a system needs to be understood as a whole. If systems are very complex, then simulation models might prove helpful in finding the most effective way to achieve a goal. The example discussed later in this paper illustrates how the best way to cut inventory in a supply chain might be to reduce disruptions to the chain rather than shorten lead times.

SIMULATION OF AN INTERNATIONAL SUPPLY CHAIN

The supply chain as a complex dynamic system

The simulation of an international supply chain demonstrates how chaos theory can be applied to the understanding of a real managerial issue. The example is drawn from the author's research into the costs of coordinating the international supply chain of a personal computer company called California Computer Technology (CCT).[4] Following Eisenhardt (1989), a case approach was used to build and test theory in an iterative manner.

The research led to a conceptualization of the supply chain as a complex, dynamic, nonlinear system. The system is subject to external disruptions, and the stages of the chain are linked by flows of goods and information, with time lags and feedback mechanisms. The complexity of interactions along the supply chain is such that one cannot easily predict how the system will operate under various conditions, but a computer model of these processes can simulate the outcome (Lant and Mezias, 1990; Morecroft 1984). Figure 1 is a simplified representation of CCT's supply chain, showing in schematic form the flows of goods and information within the model. Solid lines represent flows of goods, dotted lines flows of information.

In reality, supply chains are often much more complex than this. CCT, for example, has hundreds of vendors, three production sites, and distributors and warehouses in many countries. Corporate headquarter functions interact with vendors, the field sales organization, and the production sites. Nevertheless, the diagram does

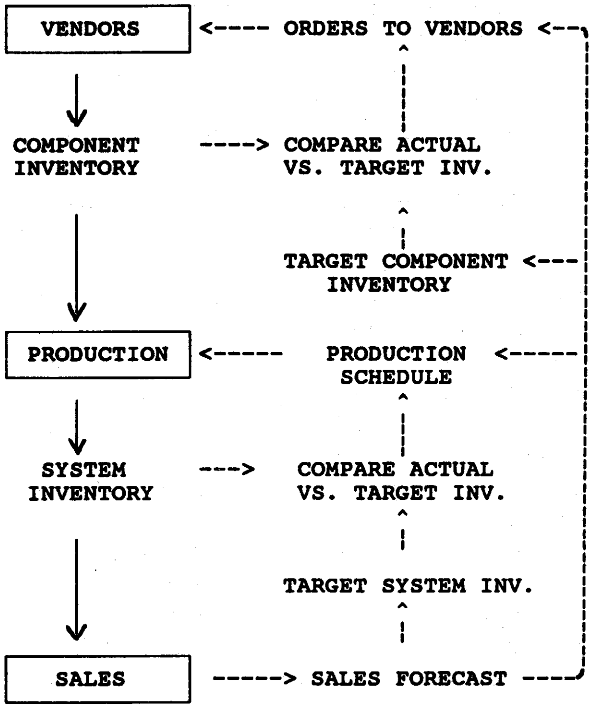

Figure 1. A Model of CCT's supply chain

capture the essence of the supply chain. Materials move along the chain in one direction, gaining value at each stage. Information is exchanged in both directions among the organizations along the chain. This simple representation is very useful in analyzing the potential sources of coordination costs in a supply chain and the impact of geographically separating stages of the chain. It is also valuable as a tool for designing strategies that improve the performance of a supply chain.

There are two important dimensions to this system, uncertainty and time relationships. Rather than performing as a stable, ready state system, each stage of the chain is potentially subject to disruptions, or 'shocks.' Demand fluctuates in an unpredictable way, production problems can affect output, and suppliers do not always deliver on time. When demand and production are rising, delivery and production problems are more likely. As a result of the uncertainty at each stage, flows of materials and finished systems fluctuate in volume, and inventories need to be adjusted to cope with the uncertainty. The linkages themselves are also subject to disruption. Shipments and communi-

[4] The name of the company has been disguised to protect proprietary information.

cation can be delayed, and information can be misunderstood.

A second important dimension of the supply chain system is the time relationship among the stages. As a result of the time lags in communication, production, and distribution, a disruption to one element generates a sequence of changes in other parts of the system. For example, demand fluctuations cause changes in sales forecasts, production schedules, and order to vendors. Disruptions originating in any one part of the system, in effect, propagate forwards and backwards along the chain. Disruptions can interact; for example, a production problem could occur in a month when demand was unexpectedly high, causing some demand to go unmet.

A number of researchers investigating aspects of the supply chain have recently turned to simulation models, most of which attempt to find cost-minimizing solutions using linear or nonlinear programming (e.g., Breitman and Lucas, 1987; Cohen and Lee, 1989; Hodder and Jucker, 1985; Hodder and Dincer, 1986). These models do not, however, deal adequately with uncertainty in a dynamic, multiperiod setting.

The simulation model developed for this study is described in more detail in the Appendix and in Levy (1992). The model assumes a set of decision rules and linkages among the stages of the supply chain, which are used to determine the production plan and other variables each month. Each stage of the supply chain is subject to random fluctuations, and the chain evolves in a dynamic fashion from month to month.

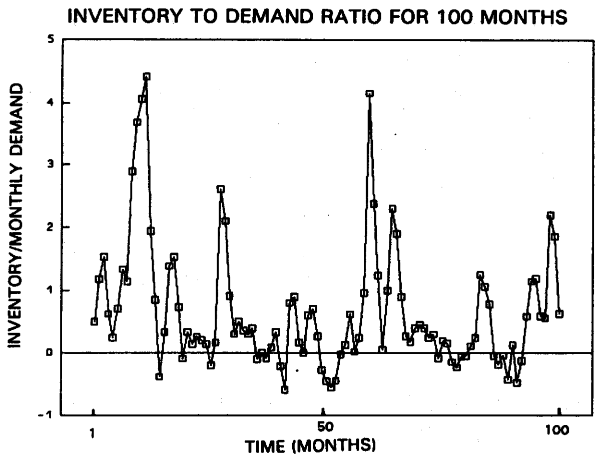

Figure 2. Simulated inventory levels, product shipped from Singapore to U.S.

Results and implications

Figure 2 shows simulated inventory levels over a period of 100 months based on a version of the model representing production in Singapore for the U.S. market, which entails 30 days shipping time. Inventory levels are expressed as a proportion of monthly demand, and negative values indicate that demand cannot be met from inventory that month.

The most obvious feature of the graph is the volatility of inventory levels. These large fluctuations illustrate well how relatively small disruptions to the supply chain can interact with organizational decision processes and lead times in the system to produce large and unpredictable outcomes. CCT's managers did not expect this volatility, because the strategic decision to source from Singapore was taken using cost estimates that assumed a stable supply chain. In fact, the instability of the chain imposed substantial unexpected costs on CCT, primarily related to the expense of using air-freight to expedite shipments, the opportunity cost of lost sales, and the cost of holding excess inventories. In addition, CCT incurred expenses relating to the communication and managerial time needed to manage the unstable supply chain. These costs were all underestimated because managers did not appreciate the impact of complex interactions along the supply chain, and tended to treat each disruption as a one-time event.

The simulation does reveal some patterns within the fluctuating inventory levels. Peak inventory levels are reached, on average, every 5 months, though the number of months between peaks varies from 2–7 months; the system is clearly aperiodic. Moreover, there is a relationship between the average time between peak inventory levels and shipping time: when production is available for sale the same month (representing production in the U.S. for the U.S. market), average time between peak inventory levels falls to around 4 months. Note also that inventory levels are less volatile and that peaks are lower, as would be expected when delivery times are shorter.

As well as illustrating the volatility of the supply chain and its associated costs, the model

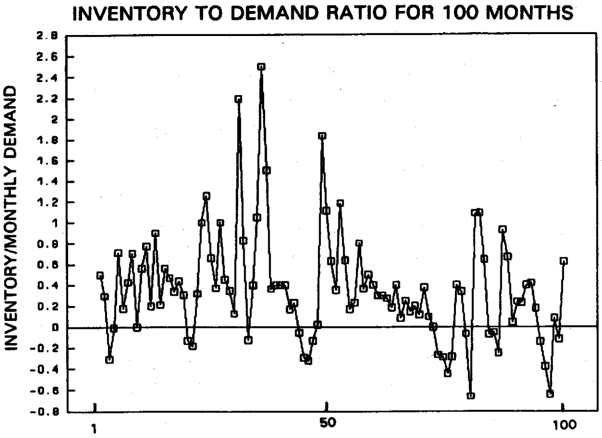

Figure 3. Simulated inventory levels, product made and sold in U.S.

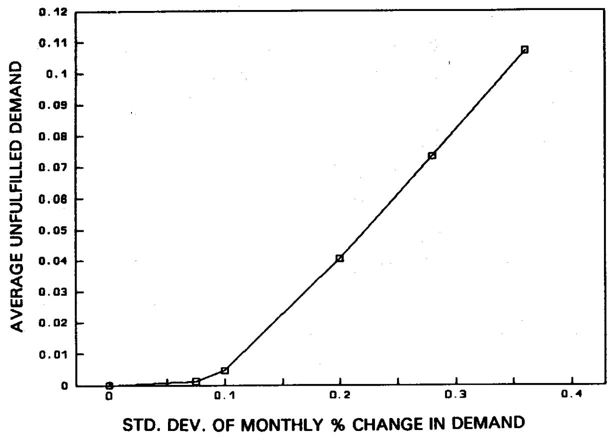

Figure 4. Impact of demand stability on unfulfilled demands

can be used to guide decisions concerning production location, sourcing, and optimum inventory levels. Used for this purpose, the simulation model demonstrates how complex systems need to be understood as a whole, and how goals can be achieved through indirect and nonobvious means. For example, the simulation model enables the cost of offshore sourcing to be estimated in terms of the incremental inventory needed to maintain demand fulfillment at some specified level. It was estimated that in order to maintain an average level of 95 percent demand fulfillment when sourcing from Singapore rather than California for the U.S. market, average system inventory levels would have to increase by more than 2 months of sales.

The underlying order in the supply chain system can be glimpsed in Figure 4. The X-axis shows the value of a parameter representing the standard deviation of the monthly percentage change in demand, a measure of demand instability. The range of values was chosen to reflect the instability observed for CCT's products. The Y-axis shows the average proportion of demand that could not be fulfilled over 100 iterations of a 36-month period.

There appears to be a threshold beneath which demand instability does not have a significant effect; in this region, the system does not exhibit chaos. Once the instability parameter approaches 0.1, the proportion of demand unfulfilled begins to rise rapidly but smoothly and exceeds 10 percent of demand for products with the most unstable demand.

While the simulation model illustrates the costs and difficulties of an unstable supply chain, it also suggests approaches to solving these problems. The simulation model could be used to determine optimal inventory levels for different products and components, and to identify those which need to be manufactured locally, based on the level of volatility associated with them. Although CCT's managers had always been aware that unstable products should be produced locally, they tended to underestimate these costs. The simulation provided a tool to analyze more precisely which products were stable enough for offshore manufacture.

Another approach, using the insight gained from Figure 4 above, would be for managers to attempt to improve the accuracy of sales forecasting in order to reduce the cost of offshore manufacture. Similarly, managers could try to reduce disruptions to the supply chain from other sources, by working with suppliers to improve quality and reduce lead times, and by reducing the occurrence of internal production problems. Volatility can also be reduced by intervening at the boundaries of the system to change its structure. CCT, for example, has participated in the widely observed trend toward fewer suppliers. Using these techniques, management could simplify and stabilize the system, possibly making it nonchaotic.

It should be noted that the approaches to managing complex systems described above constitute key elements of lean production (Womack, Jones, and Roos, 1990). Lean production can thus be conceptualized as a way to simplify and reduce the variance of complex dynamic supply chain systems, making their behavior more predictable. Indeed, this research suggests that, contrary to the prevailing notion that lean production methods constrain international production (Hoffman and Kaplinsky, 1988; Jones and Womack, 1985), lean production could actually facilitate international operations by reducing volatility along the supply chain.

CONCLUSIONS

Chaos theory is a promising framework that accounts for the dynamic evolution of industries and the complex interactions among industry actors. By conceptualizing industries as chaotic systems, a number of managerial implications can be developed. Long-term forecasting is almost impossible for chaotic systems, and dramatic change can occur unexpectedly; as a result, flexibility and adaptiveness are essential for organizations to survive. Nevertheless, chaotic systems exhibit a degree of order, enabling short-term forecasting to be undertaken and underlying patterns can be discerned. Chaos theory also points to the importance of developing guidelines and decision rules to cope with complexity, and of searching for nonobvious and indirect means to achieving goals.

The simulation model presented here demonstrates that chaos theory has practical application to issues of business strategy. The simulation illustrates how management can underestimate the impact of disruptions to an international supply chain, generating substantial unanticipated costs. It also demonstrates how management might intervene to reduce the volatility of the supply chain and improve its performance, by reducing the extent of disruptions and changing the structure of the supply chain system.

APPENDIX

The supply chain was simulated using a spreadsheet model, with columns representing the variables in the system, and rows representing successive months. In order to model the stochastic nature of the supply chain, a simulation package called 'RISK' was used, which allows a variety of probability distributions to be assigned to each cell of the spreadsheet. Actual data and decision criteria from CCT were used to determine the structure of the model and the range of values to be used for various parameters. For example, monthly bookings data revealed that the level of bookings each month could be modeled by taking the previous month's demand plus a percentage change that was a normally distributed random variable with mean zero.

Three sets of input parameters were used for the model. The first set represents the level of disruptions affecting demand, supplier deliveries, and production. The second set represents the target levels of system and component inventories. The standard values for these were set at half a month's sales for systems, excluding any inventory in transit, and 1 week's production for components. The third group of input parameters represents the impact of distance on shipping time for finished goods, and of different vendor lead times. The main output variables of the system were the levels of system and component inventories and the level of demand fulfillment. Using these parameters, the model simulates a 36-month time period. The model begins at time zero with a nominal level of demand and production of 100 units, but these values evolve over time. The simulation package enables the spreadsheet to be recalculated a specified number of times. On each iteration, the entire 36-month spreadsheet is recalculated with a new set of random numbers. A large number of iterations can thus be used to build up a probability distribution for these output variables and to calculate a mean (expected) value. The results presented here were obtained using one hundred iterations for each simulation. Each simulation of 100 iterations was run using a different set of input parameters. A list of variables recalculated on a monthly basis is given in the Appendix.

Three main performance measures were captured as output variables. Average system and average component inventory levels over 100 iterations of the 36-month period were expressed in terms of months' sales. Demand fulfillment was measured by summing the total number of units of demand which could not be met due to inadequate inventory, and dividing this total by total demand to give a ratio indicating unfulfilled demand.

The effect of distance on shipping times and of different vendor lead times was modeled by using different versions of the basic model. The simulations used for this paper used a version in which production in Singapore is available for sale in the U.S. the following month (i.e., 30 days to ship and clear customs) and vendor lead times are 60 days.

VARIABLES RECALCULATED ON MONTHLY BASIS FOR SIMULATION MODEL

ACTUAL DEMAND: Demand for systems each month was equal to the previous month's demand plus a random percentage change.

ACTUAL SALES: Sales of systems each month were equal to demand unless constrained by lack of inventory.

SALES FORECAST: The best sales forecast for the next month was the previous month's demand, as no trend was built into demand fluctuations.

ENDING COMP. INV.: The level of component (or material) inventory each month was the level the previous month plus deliveries from vendors less whatever was consumed in production.

TARGET COMP. INV.: The target level of component inventory was adjusted each month to equal a proportion of the current sales forecast.

ORDERS TO VENDORS: Orders to vendors were based on the sales forecast, the production schedule for the following month, and a comparison of actual with target component inventory levels.

DEL. FROM VENDORS: Deliveries each month equalled orders placed 1 or 2 months previously, depending on the version, less a random percentage.

ENDING SYSTEM INV: System inventory at the end of each month was equal to the inventory the previous month less sales plus production the same or the previous month, depending on the model version.

TARGET SYSTEM INV: The target level of system inventory was adjusted each month to equal a proportion of the current sales forecast.

PRODUCTION PLAN: The production plan for the following month was based on the sales forecast, adjusted for the difference between actual and planned system inventory.

ACTUAL PRODUCTION: System production each month was equal to the production plan of the previous month, less a random percentage, and constrained by the availability of material inventory.

UNFUL. DEMAND: Unfulfilled demand equalled monthly demand less monthly sales.

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