APPLICATIONS OF CHAOS AND COMPLEXITY THEORIES TO THE TECHNOLOGY ADOPTION LIFE CYCLE: Case studies in the hard-drive, microprocessor, and server high-tech industries.

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Abstract

Strategy formulation for high-technology products is very difficult. The short life cycles, and rapidly changing technology make it extremely challenging to develop and implement successful product strategy. Additionally, since the high-tech market is an example of a complex system, its behavior is an emergent property of component interactions. The continual co-evolution of system components with respect to each other and the environment creates a highly non-linear dynamical system. This paper introduces a quantitative approach to understand the product position in the technology adoption life cycle using some of the principles and tools of Chaos and Complexity theories. This approach is demonstrated by using data sets of three case studies in the hard-drive, microprocessor, and server high-tech industries.

1. Introduction

The high-tech industry is central to the nation's economic competitiveness and national defense (National Science Foundation, 1988; Office of Technology Assessment, 1982). Nevertheless, manufacturers of high-tech products find it challenging to develop and implement successful technology-adoption-life-cycle strategies (Anders, 1999; Brockhoff and Chakrabarti, 1988; Brody, 1991; Christensen, 1997; Ferrary, 2003; Filson, 2000; Gardner et al., 2000; McGrath, 1995; Modis, 1998; Noten et al., 2005; Watanabe et al., 2005). Rapid turnaround and changing technology are two of the reasons for that challenge. In a 1999 speech, Alan Greenspan (1999) provided a third reason when he said, "Despite the remarkable progress witnessed to date, we have to be quite modest about our ability to project the future of technology and its implications for productivity growth and for the broader economy." In other words, history is not necessarily a good predictor of the future in the high-tech arena.

We believe that the poor predictive capability derives from the fact that the high-tech market is a non-linear, dynamic system. Hence, its behavior is an emergent property that results from the endogenous interactions of its many components and their exogenous interactions with the outside world (Bewley and Griffiths, 2001; Danaher et al, 2001; Dietrich and Shipley, 1999; Doherty and Delener, 2001; Golder and Tellis, 1998; Kelly and Allison, 1999; Koch, 1999; Lucas, 2001; Phelan, 1995; Sterman, 2000). This means that traditional approaches such as forecasting or time series analysis cannot predict accurately its future states (Hanssens et al., 1990; Maier, 1998; Meade and Islam, 1998; Xie et al., 1997). In this paper, we propose a new approach to modeling the market based on Chaos Theory (Gleick, 1988) and Complexity Theory (Vriend, 1994; Langton et al., 1994; Wolfram 1986). We will show that this approach provides a better assessment of a product's position within its lifecycle and that this assessment provides the basis for better technology adoption strategy.

The paper is organized as follows. First, we discuss the state-of-the-art. Next, we explain the attractor framework in detail and its validation using actual data from several case studies from the hard-disk and the microprocessors industries. Finally, we present conclusions and proposed future work.

2. The Technology Adoption Life Cycle

In today's dynamic, high-tech markets, product strategy is even more critical than in other industries (Christensen, 1997; Christensen, 2003; Cooper, 2000). This strategy cannot be static, because markets continuously reward or punish companies based primarily on their product's performance. That performance depends, to a large extent, on the success or failure of the company's product strategy. In developing such a successful strategy, companies face many challenges including new technologies, new customer requirements, and new competitors' products, to name a few. These challenges have forced companies to learn how to manage short and rapidly changing product and market lifecycles. Because of this, companies have placed more emphasis on understanding the technology adoption lifecycle (Moore, 1999a; Moore, 1999b; O'Connor, 2002).

The technology adoption life cycle is a means for classifying the market and its reaction to a high-tech product (See Figure 1). That classification is based loosely on a common classification, which identifies consumers' sensitivity to risk. That classification has five classes, which appear and disappear over the life of the product: innovators, early adopters, early majority, late majority or laggards (Moore, 1999a). Each class has a different set of needs, product criteria, reactions to new innovations, and marketing approaches.

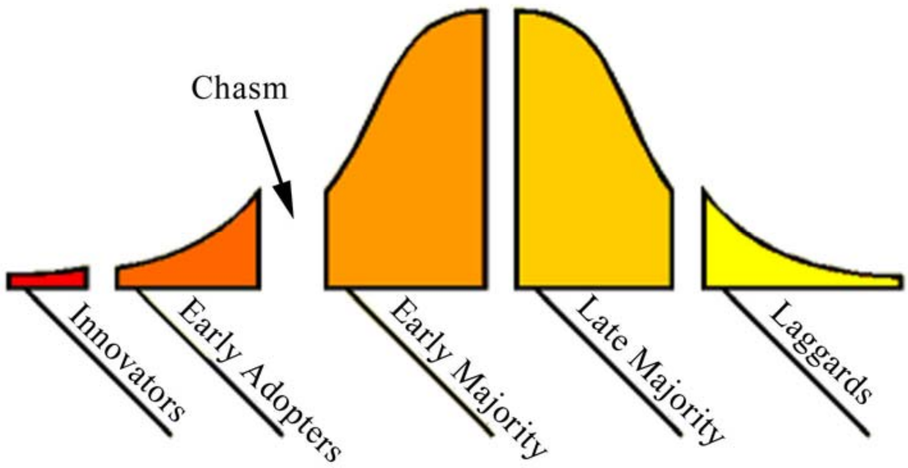

Figure 1. The technology adoption life cycle and the different phases.

To define the technology adoption life cycle, we use the approach described in Moore (1999b). Moore defined 6 discrete stages: Innovation, Chasm, Tornado, Main Street, Decline, and Obsolescence (see Figure 2). The transitions between these stages are determined from the inflection rate ***I*** in the curve. A line with slope of ±1 defines the inflection rate. When the slope of the life-cycle curve intersects this line, an inflection point exists and a transition occurs. Since the derivative of a curve at a point is equal to the slope of the tangent line at that point, we can write the equation for the inflection rate as:

$$\boldsymbol{I} = \frac{\partial \xi}{\partial t} \tag{1}$$

Where ξ is a function describing the technology adoption life cycle curve. ξ_{Max} is the maximum value achieved on the y-axis for the technology adoption life cycle.

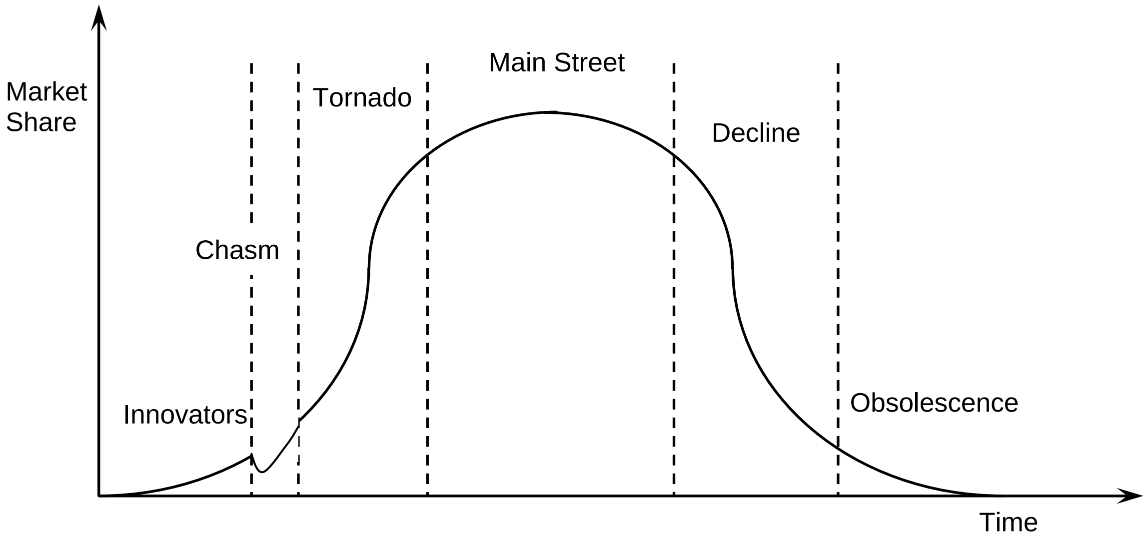

Figure 2. Life cycle phases based on Moore (1999b).

3. Positioning within the Technology Adoption Life Cycle

Companies base pricing and marketing strategies on the position of a product on this curve. Moore hinted at the importance of this position when he said, "significant marketing expenditure and risk ultimately hinge on a choice about where the product is in the Technology Adoption Life Cycle" (Moore, 1999b). Unfortunately, reliable quantitative methods for identifying the current position directly do not exist (Brownlie, 1992; Holger, 1998; Jensen, 2001; Lapide, 2001; Levitt, 1986; McGrath, 1995; Meade, 2003; Modis, 1998; Moore, 1999b; O'Connor, 2002; Shanklin and Ryans, 1994; Swanson et al., 1997; Walsh et al., 2005). Consequently, the primary means of determining a product's position is to draw a correlation with the product's diffusion into the market.

The literature is flooded with models for forecasting a product's diffusion into the market. The majority of them are based on the Bass (1969) model, which generalizes two earlier models developed by Fourt and Woodlock (1960) and Mansfield (1961). These newer models extend the Bass model by including additional marketing-mix factors as parameters (Jensen, 2001; Golder and Tellis, 1998; Lapide, 2001; Mahajan and Wind, 1986; Swanson et al., 1997). A common problem with these models is that their forecasts are based upon parameters, which must be estimated. Furthermore, the performance of a given model is limited to those situations meeting its necessary assumptions and data characteristics.

Additionally, the majority of the known models are based on time. Therefore, rather than providing insight into the current position of the product based on current environmental factors, the model merely indicates where in the diffusion curve the product should be at a given time. For time invariant models, this forecast of where in the lifecycle the product should be was made at the very beginning of the lifecycle and based upon estimates for the parameters.

Finally, very few of the reviewed models are designed specifically for high-tech products. It is a generally accepted fact that high-tech products experience a slightly different adoption lifecycle, with shorter life spans and greater product volatility. None of the models account for the presence of a chasm, or the substantive influence of the existing technology infrastructure and OEM’s on adoption. Rather than modeling the technology adoption life cycle as being a function of risk tolerance versus value proposition as most high-tech marketing experts claim, the existing models view adoption as a function primarily of the influence of other users and marketing-mix (Levitt, 1986).

4. Our Approach

4.1 The Attractor Framework

We believe that a crucial factor is missing in all these models: the complex and fundamentally non-linear and dynamic nature of the market. To address this, we propose to use the attractor framework developed by researchers in the fields of chaos and complexity (Gleick, 1988; Holland, 1995; Kauffman, 1991, 1993, 1995; Lefebvre and Letiche, 1999; Wuensche, 1999). Conceptually, an attractor is a set of values in phase space to which a system migrates over time, or about which the system iterates (this has similarities with the technology adoption life cycle). It is created by plotting the derivative of the curve evaluated at a given point against the point itself or $\frac{\partial x(t)}{\partial t}$ vs. x(t). It can be a single fixed point, a collection of points regularly visited, a loop, a path, a complex orbit, or an infinite number of points and it can have as many dimensions as the number of variables that influence it.

The variable we chose was % of Market Share. This is a good choice because it not only provides a systematic view of the product life cycle, but it also inherently conveys information about competitors and their products, which drive the adaptation within the market and create complexity. It was initially thought that multiple variables would be necessary to properly characterize the system. However, research revealed that additional variables (e.g., sales, rate of change in sales, shipments, profitability, rate of change in profitability, number of competitors, etc.) overcomplicated the framework and did not add additional fidelity (Meade, 2003). The elegant simplicity of this attractor enables easy implementation of the framework. To demonstrate this construct on an actual data set, consider the attractor of the 5.25” hard disk (Disk/Trend, Inc., 1976-1998) shown in Figure 3. It is clear from the analysis of successive generations of hard drives that the phases of the technology adoption life cycle coincide with specific regions of its attractor, thus enabling the attractor to serve as an excellent indicator of a product's position within its life cycle. This attractor turned out to be stable and cyclic.

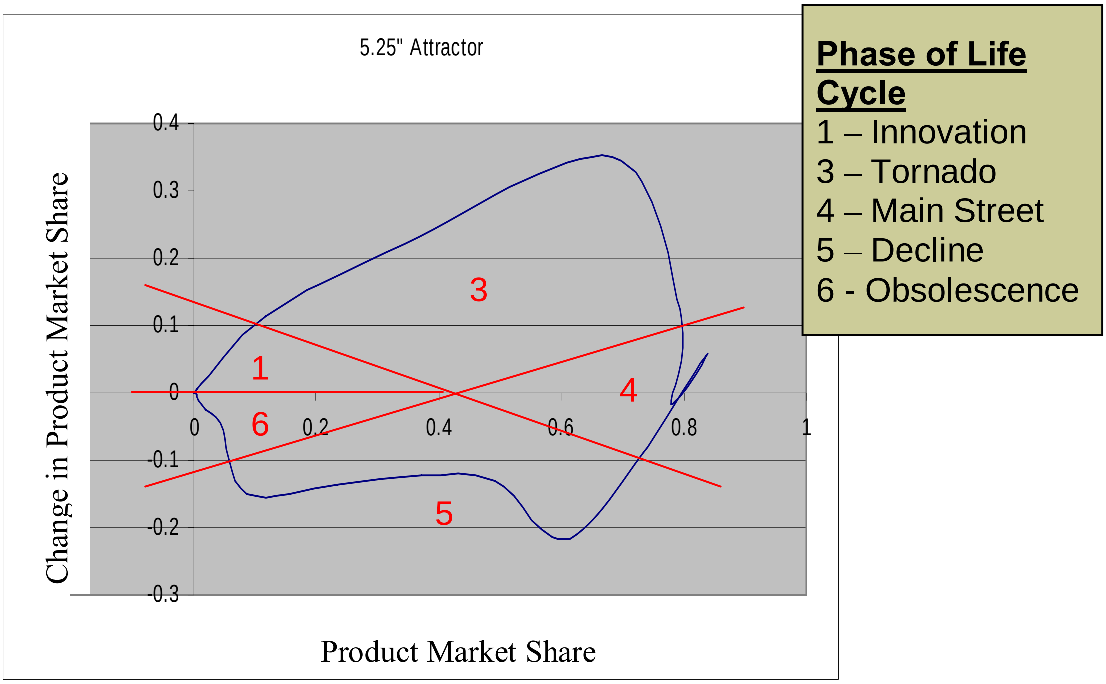

Figure 3. Attractor for the 5.25" disk (Yearly Data).

4.2 Using the Attractor to Position the Product

Recall that stage changes in the technology adoption curve are determined by the inflection rate of change in market share ***I***. Since we are using actual data points and do not have a mathematical description for the curve, we need a new approach. This new approach assumes a symmetrical life cycle and uses a modified algebraic description of a 45^{o} tangent line to the curve. The inflection point can now be computed using equation 2, where MS_{Max} is maximum market share and *AP* is the number of periods in the life cycle, which is also the attractor period:

$$\boldsymbol{I} = \frac{MS_{Max}}{\left(\frac{AP}{2}\right)} \tag{2}$$

The inflection rate $\boldsymbol{I}$ is calculated for an industry using historical data from representative products that have completed their entire life cycles. All calculations are performed using industry wide data – not product data from an individual manufacturer. It is essential to use industry data to determine the true life cycle of the product rather than the individual performance of a single competitor. Consequently, both MS_{Max} and AP are determined from existing historical data and do not require any prediction regarding future product sales. This is possible for two reasons. First, MS_{Max} is looking at the product market share as a percentage of total industry sales. This means that the market can grow in size over time without affecting the relative percentage of market share that an individual product generation is capable of capturing. Second, industries tend to be relatively stable across product generations. For example, the life cycle curves for both the hard drive industry and the microprocessor industry are fairly similar in both life cycle duration and maximum market share. These two statistics tend to be factors intrinsic to an industry and change only when the market itself changes. Consequently, they remain constant across product generations and provide a stable basis for creating the attractor

The inflection rates along with the stable nature of the attractor allow an idealized model to be created for determining a product's phase in the life cycle. This construct can easily be applied to any product with only 2 time periods of market share data. In order to properly scale the model, however, it is necessary to understand the industry attractor. The industry attractor enables the calculation of $\boldsymbol{I}$ by establishing what the maximum market share and attractor period for the industry are. Once $\boldsymbol{I}$ has been properly determined, the various phases on the industry attractor can be identified. By plotting the market share and change in market share for a product it is possible to see what phase of the industry attractor the point falls in.

This attractor developed for the Disk Drive industry using the data of the 5.25” disk (Figure 3) was tested with the data of the 14”, 10”, 9.5”, 6.25”, 3.25”, 2.5”, and 1.8” disks. This data was obtained from 22 marketing reports from Disk/Trend, Inc. (1976-1998) covering the hard disk industry over a 22 year period of time from 1976 – 1998. Disk/Trend, Inc. is the publisher of the most widely used market studies on the worldwide disk drive industry. This attractor framework was able to provide the positions of these disks at different times of their life cycle with 100% accuracy (see Table 1). Consequently, this attractor can be presented in an idealized and visual/graphics construct as shown in Figure 4.

Table 1. Prediction of the position in the Technology Adoption Life Cycle (TALC) using the Attractor Framework for the 6.5”, 9.5”, 10”, and 14” disks. MS is Market Share, MS’ is rate of change in Market Share, Max MS is Maximum Market Share, and Min MS’ is minimum rate of change in Market Share. The following cycles are presented by the respective numbers: 1 – Innovation, 3 – Tornado, 4 – Main Street, 5 – Decline, and 6 – Obsolescence.

	Year	MS	MS'	Max MS	Min MS'	TALC		Predicted		Error
6.5" - 9.5"	1979	11.94%	11.94%	11.94%	11.94%	3		3		0
	1980	33.05%	21.11%	33.05%	11.94%	3		3		0
	1981	41.11%	8.06%	41.11%	8.06%	4		4		0
	1982	35.95%	-5.16%	41.11%	-5.16%	4		4		0
	1983	16.45%	-19.50%	41.11%	-19.50%	5		5		0
	1984	8.72%	-7.74%	41.11%	-19.50%	6		6		0
	1985	6.38%	-2.34%	41.11%	-19.50%	6		6		0
	1986	*4.46%*	-1.91%	41.11%	-19.50%	6		6		0
	1987	*2.50%*	-1.97%	41.11%	-19.50%	6		6		0
	1988	2.34%	-0.16%	41.11%	-19.50%	6		6		0
	1989	1.74%	-0.60%	41.11%	-19.50%	6		6		0
	1990	1.20%	-0.54%	41.11%	-19.50%	6		6		0
	1991	0.83%	-0.38%	41.11%	-19.50%	6		6		0
	1992	0.36%	-0.47%	41.11%	-19.50%	6		6		0
	1993	0.20%	-0.16%	41.11%	-19.50%	6		6		0
	1994	0.11%	-0.09%	41.11%	-19.50%	6		6		0
	1995	0.01%	-0.10%	41.11%	-19.50%	6		6		0
	1996	0.01%	0.00%	41.11%	-19.50%	6		6		0
	1997	0.00%	-0.01%	41.11%	-19.50%	6		6		0
10' - 14"	1976	100.00%	100.00%	100.00%	100.00%	3		3		0
	1977	100.00%	0.00%	100.00%	0.00%	4		4		0
	1978	100.00%	0.00%	100.00%	0.00%	4		4		0
	1979	88.06%	-11.94%	100.00%	-11.94%	5		5		0
	1980	66.44%	-21.62%	100.00%	-21.62%	5		5		0
	1981	46.95%	-19.49%	100.00%	-21.62%	5		5		0
	1982	30.54%	-16.41%	100.00%	-21.62%	5		5		0
	1983	14.99%	-15.55%	100.00%	-21.62%	5		5		0
	1984	9.73%	-5.26%	100.00%	-21.62%	6		6		0
	1985	7.90%	-1.83%	100.00%	-21.62%	6		6		0
	1986	4.65%	-3.25%	100.00%	-21.62%	6		6		0
	1987	2.43%	-2.23%	100.00%	-21.62%	6		6		0
	1988	1.88%	-0.55%	100.00%	-21.62%	6		6		0
	1989	*1.07%*	-0.81%	100.00%	-21.62%	6		6		0
	1990	*0.79%*	-0.28%	100.00%	-21.62%	6		6		0
	1991	0.49%	-0.30%	100.00%	-21.62%	6		6		0
	1992	0.23%	-0.26%	100.00%	-21.62%	6		6		0
	1993	0.15%	-0.07%	100.00%	-21.62%	6		6		0
	1994	0.07%	-0.09%	100.00%	-21.62%	6		6		0
	1995	0.01%	-0.06%	100.00%	-21.62%	6		6		0

Total Error	0

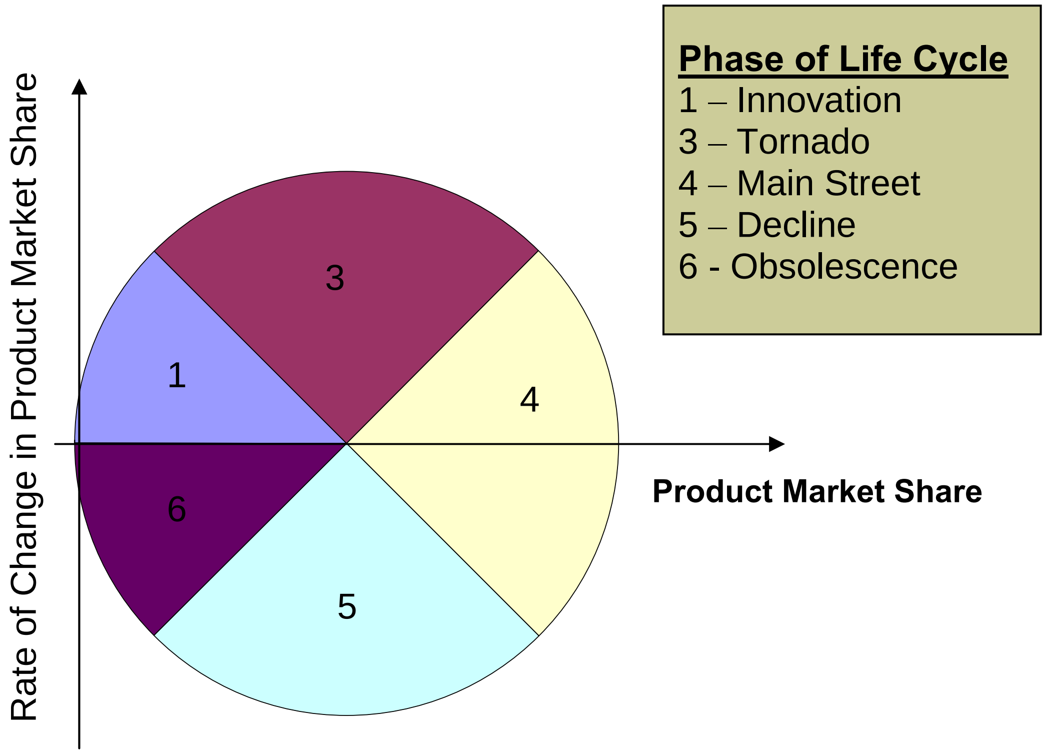

Figure 4. Idealized Attractor Framework.

The corresponding visual/graphics representation of the Attractor Framework was transformed by using classification trees (Breiman et al., 1984) to a set of rules. This rule-based representation for the Attractor Framework is done by using various views of the product's market share:

- Product market share
- Change in product market share
- Maximum product market share achieved to date
- Minimum change in product market share to date

The basis for the decisions within the rules consequently hinge on comparisons with 2 key variables. The first variable is the inflection rate **I** as defined earlier. The second variable is the center point for the industry attractor **C**. This is the same as that used earlier in defining the technology adoption life cycle. This is used to distinguish between the first half and second half of the life cycle and distinguish between products that are successful and those who never emerge from the chasm and ultimately die. The center point is merely found by dividing the maximum average market share by two. There is typically a large degree of latitude in the assignment of the center point, but the inflection rate is very sensitive to the numbers used in its calculation. The rules are presented in Figure 5. Therefore, the decision-maker has the option to use the visuals (graphics) (Figure 4) or the set of rules (Figure 5) to apply the Attractor Framework.

α – Product market share
β – Change in product market share
χ – Maximum product market share achieved to date
δ – Minimum change in product market share to date
I – Inflection rate
C – Center point

IF (β > I) THEN *Tornado*
IF (β < I) And (β <= -I) THEN *Decline*
IF (β < I) And (β > -I) And (α >= C) THEN *Main Street*
IF (β < I) And (β > -I) And (α < C) And (χ >= C) THEN *Obsolescence*
IF (β < I) And (β > -I) And (α < C) And (χ < C) And (δ >= 0)THEN *Innovation*
IF (β < I) And (β > -I) And (α < C) And (χ < C) And (δ < 0)THEN *Chasm*

Figure 5. Rule-based representation of the Attractor Framework.

5. Cross Validation

Given the excellent results of the attractor framework within the hard drive industry, it was decided to cross validate the results with a second industry to determine its general applicability. For such an analysis it is desirable to use an industry which experienced a high number of product evolutions in a relatively short period of time. Consequently, it was decided that the microprocessor industry would be an ideal candidate (A market report entitled “Annual Wrap Up: Intel Microprocessors Service” was purchased from In-StatMDR and provides all of the microprocessor data from 1993 to 2002 used within this research). Due to the rapid rate of innovation within the industry striving to keep pace with Moore’s Law (Moore, 1965), the microprocessor industry typically realizes a new product introduction every 18 months (see Table 2).

Table 2. Intel product roadmap and the Moore's Law (In-StatMDR (2003)).

Architecture	Core	Introduction	MhZ	IC Process (micron)	Number of Transistors (M)
80486	DX	Apr-89	25	1.2	0.8
		May-90	33		
		Jun-91	50		
	DX2	Aug-92	66		
	DX4	Mar-94	100	0.6	
Pentium		Mar-93	66	0.8	3.2
		Jul-94	100	0.6	
		Mar-95	120		
		Jun-95	133	.35	3.3
		Jun-96	166		
		Jun-96	200		
	MMX	Jan-97	200		4.5
		Jun-97	233		
Pentium Pro		Nov-95	200	0.35	5.5
Pentium II	Klamath	May-97	300	0.35	7.5
	Deschutes	Jan-98	333	0.25	
	Mendocino	Aug-98	300		19
Pentium III	Katmai	Feb-99	500	0.25	9.5
	Coppermine	Oct-99	733	0.18	28
	Cascades	Mar-00	1000		
Pentium 4	Willamette	Nov-00	1500	0.18	42
		Sep-01	2000		
	Northwood	Jan-03	2200	0.13	55
		May-03	2533		
		Nov-03	3000		
Itanium	Merced	May-03	800	0.18	300
Itanium 2	McKinley	Jul-03	1000	0.18	222

The individual product market shares for the Pentium, Pentium II and Pentium III microprocessors were determined, and then the per time period rate of change was calculated. This data was then used to graph their attractors. As expected, this attractor is very stable and provides an excellent means for capturing the dynamics of the market. The inflection rate was calculated to be 7.69%. Figure 6 shows the attractors of the different microprocessors. It is possible to see the high number of points clustered around the inflection rate. Again, the prediction rate of the attractor was very high with 99% accuracy (see Table 3).

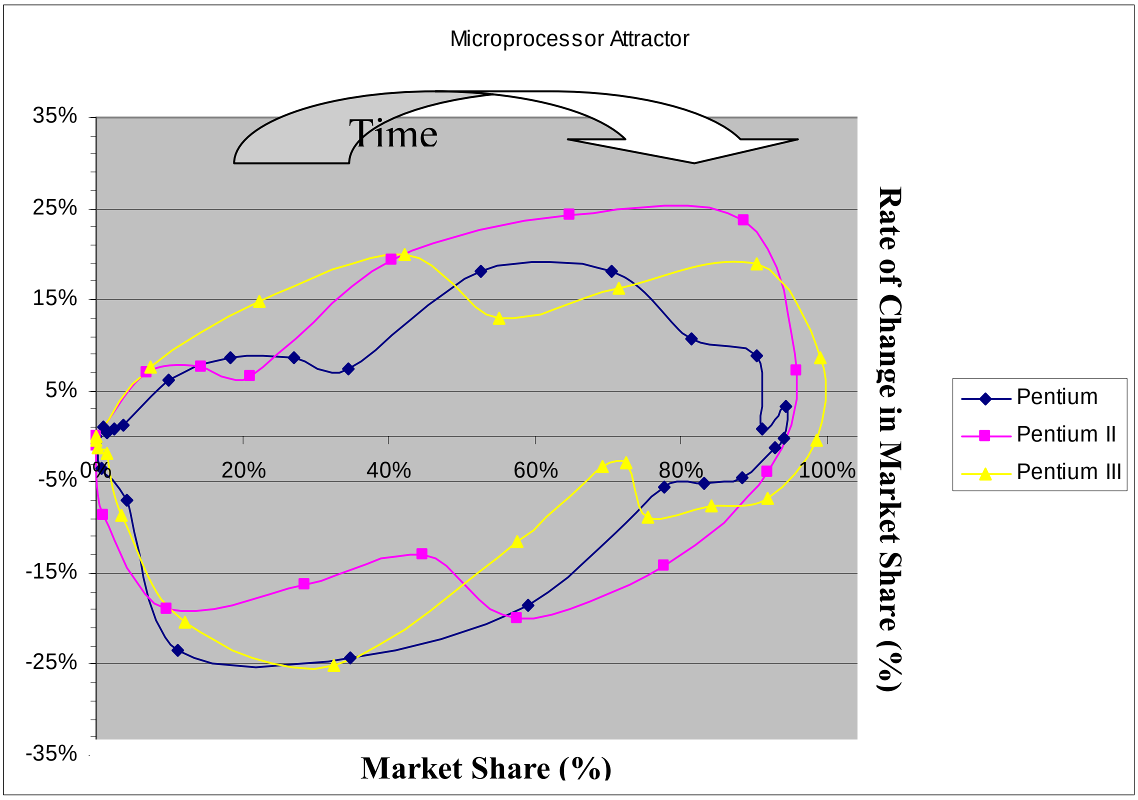

Figure 6. Attractors with Inflection Rate for the Pentiums (Rate of Change in Product Market Share Vs Market Share (Quarterly Data))

Due to the high number of points clustered around the inflection points, there is a greater opportunity for error when applying this model. Slight variations in the numbers used to calculate the industry attractor's inflection rate can move a point from one phase to another. The reason for this clustering is the resolution of this data set. The microprocessor data is quarterly, as opposed to the hard drive data which is yearly. As the life cycle approaches the inflection point, there is a natural tendency to hover periodically near the inflection rate prior to entering the next phase. This is a result of the positive and negative feedback loops which create the non-linear dynamics of the system. Just prior to reaching the tipping point, these two loops are in an unstable equilibrium. The system briefly maintains this equilibrium before being plunged into the next phase by the dominance of one of the feedback loops over the other. The increased resolution provides the ability to capture this brief period of unstable equilibrium. A lower resolution does not pick up on this and results in a larger and clearer difference in the points in each phase. Once the balance of power shifts between feedback loops the entire system moves quickly to obey the dominant loop.

Table 3. Prediction of the position in the Technology Adoption Life Cycle (TALC) using the Attractor Framework for the Pentium III. MS is Market Share, MS' is rate of change in Market Share, Max MS is Maximum Market Share, and Min MS' is minimum rate of change in Market Share. The following cycles are presented by the respective numbers: 1 – Innovation, 3 – Tornado, 4 – Main Street, 5 – Decline, and 6 – Obsolescence.

	Year	MS	MS'	Max MS	Min MS'	TALC	Predicted	Error
Pentium III	4Q98	0.00%	0.00%	0.00%	0.00%	1	1	0
	1Q99	7.54%	7.54%	7.54%	0.00%	1	1	0
	2Q99	22.38%	14.84%	22.38%	0.00%	3	3	0
	3Q99	42.28%	19.90%	42.28%	0.00%	3	3	0
	4Q99	55.21%	12.93%	55.21%	0.00%	3	3	0
	1Q00	71.54%	16.33%	71.54%	0.00%	3	3	0
	2Q00	90.41%	18.87%	90.41%	0.00%	3	3	0
	3Q00	99.04%	8.63%	99.04%	0.00%	3	3	0
	4Q00	98.62%	-0.42%	99.04%	-0.42%	4	4	0
	1Q01	91.91%	-6.71%	99.04%	-6.71%	4	4	0
	2Q01	84.26%	-7.65%	99.04%	-7.65%	4	4	0
	3Q01	75.39%	-8.87%	99.04%	-8.87%	5	5	0
	4Q01	72.50%	-2.89%	99.04%	-8.87%	4	4	0
	1Q02	69.18%	-3.33%	99.04%	-8.87%	4	4	0
	2Q02	57.56%	-11.62%	99.04%	-11.62%	5	5	0
	3Q02	32.46%	-25.09%	99.04%	-25.09%	5	5	0
	4Q02	12.10%	-20.36%	99.04%	-25.09%	5	5	0
	1Q03	3.51%	-8.60%	99.04%	-25.09%	5	5	0
	2Q03	1.61%	-1.89%	99.04%	-25.09%	6	6	0
	3Q03	0.33%	-1.29%	99.04%	-25.09%	6	6	0
	4Q03	0.00%	-0.33%	99.04%	-25.09%	6	6	0
	1Q04	0.00%	0.00%	99.04%	-25.09%	6	6	0

Total Error	0

6. Market Segmentation

As implied above, the attractor framework can also be applied to an individual market segment. By scaling the attractor model to the size of the market segment, it is possible to calculate the inflection rate and determine the product's position within its life cycle. This was demonstrated by applying the model to the server market segment within the microprocessor industry. Consequently, it is possible to track a product's life cycle as a whole, and as a competitor within a specific segment of the market. This allows the development of segment specific marketing, pricing and product strategies.

The challenge to applying this framework to a market segment in the microprocessor industry lies in the fact that Intel will sell the same core into multiple market segments. For example, the same Deschutes core was used for both the Desktop Performance market as a Pentium II and also the Desktop Value market as the Celeron.

The data available did not provide sales per unit by market segment, so this limited the degree to which market segmentation could be explored. However, there were 3 cores which were sold exclusively into the workstation and server markets. These were the Cascades, Foster, and Merced. The Merced core was the first generation of the Itanium processor which was Intel's proof of concept for a 64 bit processor. This particular chip experienced significant problems and sold very poorly. However, by including this processor in the analysis it is possible to see how the model reacts to a product failure.

For the analysis of an individual market segment, it is necessary to know the expected market share of that segment. Since the data included the full life cycles of the 3 products, it was possible to determine that the average maximum market share achieved by an individual product competing in the server market segment was about 1.2% of the total market. The AP was determined from the data to be approximately 10 months. It should be noted that the Merced chip was not included in this calculation since it was a failed product.

We must now rescale the attractor model to the smaller size of the market segment. From equation 2 we have:

$$\mathbf{I} = \frac{MS_{Max}}{\left(\frac{AP}{2}\right)} = \frac{1.2}{\left(\frac{10}{2}\right)} = 0.24\% \tag{3}$$

and

$$\mathbf{C} = \frac{MS_{Max}}{(2)} = \frac{1.2}{2} = 0.6\% \tag{4}$$

The product attractors are shown in Figure 7. When the attractor framework was applied to the data, it proved to be 100% accurate in determining the current phase of the technology adoption life cycle (see Table 4).

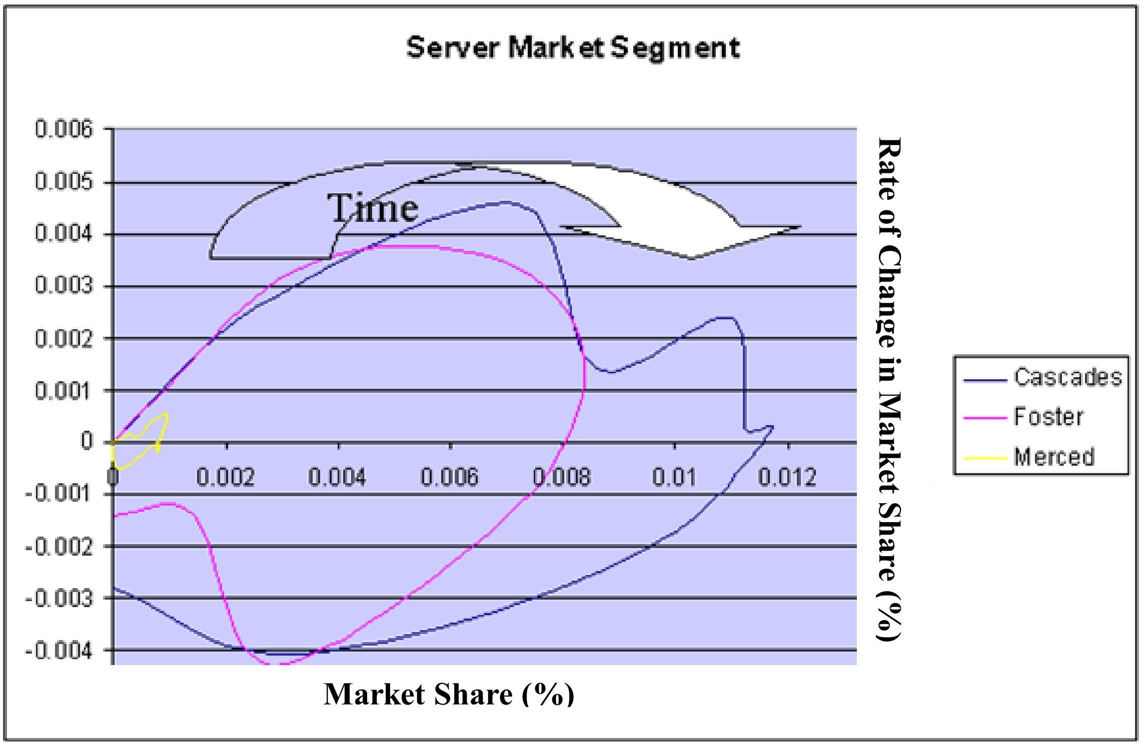

Figure 7. Server Market Segment Attractor (Market Share Vs Rate of Change in Product Market Share (Quarterly Data)).

Table 4. Prediction of the position in the Technology Adoption Life Cycle (TALC) using the Attractor Framework for the server market. MS is Market Share, MS' is rate of change in Market Share, Max MS is Maximum Market Share, and Min MS' is minimum rate of change in Market Share. The following cycles are presented by the respective numbers: 1 – Innovation, 3 – Tornado, 4 – Main Street, 5 – Decline, and 6 – Obsolescence.

	Year	MS	MS'	Max MS	Min MS'	TALC	Predicted	Error
Cascades	1Q00	0	0	0.00%	0.00%	1	1	0
	2Q00	0.26%	0.26%	0.26%	0.00%	3	3	0
	3Q00	0.72%	0.46%	0.72%	0.00%	3	3	0
	4Q00	0.86%	0.14%	0.86%	0.00%	4	4	0
	1Q01	1.10%	0.24%	1.10%	0.00%	4	4	0
	4Q98	1.12%	0.02%	1.12%	0.00%	4	4	0
	1Q99	1.15%	0.02%	1.15%	0.00%	4	4	0
	2Q99	1.17%	0.03%	1.17%	0.00%	4	4	0
	3Q99	1.01%	-0.17%	1.17%	-0.17%	4	4	0
	4Q99	0.69%	-0.32%	1.17%	-0.32%	5	5	0
	1Q00	0.28%	-0.41%	1.17%	-0.41%	5	5	0
	2Q00	0	-0.28%	1.17%	-0.41%	5	5	0
Foster	4Q01	0	0	0.00%	0.00%	1	1	0
	1Q02	0.34%	0.34%	0.34%	0.00%	3	3	0
	2Q02	0.69%	0.35%	0.69%	0.00%	3	3	0
	3Q02	0.84%	0.15%	0.84%	0.00%	4	4	0
	4Q02	0.71%	-0.13%	0.84%	-0.13%	4	4	0
	1Q03	0.29%	-0.43%	0.84%	-0.43%	5	5	0
	2Q03	0.14%	-0.14%	0.84%	-0.43%	6	6	0
	3Q03	0	-0.14%	0.84%	-0.43%	6	6	0
Merced	1Q02	0	0	0.00%	0.00%	1	1	0
	2Q02	0.01%	0.01%	0.01%	0.00%	1	1	0
	3Q02	0.02%	0.01%	0.02%	0.00%	1	1	0
	4Q02	0.03%	0.02%	0.03%	0.00%	1	1	0
	1Q03	0.04%	0.01%	0.04%	0.00%	1	1	0
	2Q03	0.10%	0.06%	0.10%	0.00%	1	1	0
	3Q03	0.08%	-0.02%	0.10%	-0.02%	2	2	0
	4Q03	0.08%	0.00%	0.10%	-0.02%	2	2	0
	1Q04	0.05%	-0.02%	0.10%	-0.02%	2	2	0
	2Q04	0.01%	-0.05%	0.10%	-0.05%	2	2	0
	3Q04	0	-0.01%	0.10%	-0.05%	2	2	0

Total Error	**0**

7. Conclusions and Current Research Issues

The framework presented in this paper addresses the non-linear nature of the high-tech market and provides a quantitative means for determining a product's position within its life cycle. This research has proven that it is possible to quantitatively determine a product's position within the technology adoption life cycle by tracking its position along its attractor cycle. This position can be determined with only 1 variable and 2 data points, thus eliminating the need for large amounts of historical data. No knowledge of the system end state (i.e. total units to be sold) is required, which eliminates the need for risky guesses to be made as a basis for the model. This model proved extremely effective in determining a product's current position and was tested on both the hard drive industry and the microprocessor industry.

While extensive research has been performed to develop a generic framework for analyzing the technology adoption life cycle, much work still remains. As previously stated, this is the first application of chaos and complexity theory to product strategy. It would be impossible to exhaust all avenues of exploration in a single study. The logical next steps in this investigation are listed below.

Forecasting Phase Transitions

Additional work is also needed to develop a means for forecasting inflection points and the introduction of disruptive technologies. The ability to forecast inflection points would enable strategic positioning and give firms the ability to begin ramp up of marketing and pricing plans to support phase transitions. This would soften the effects of phase transitions, allowing greater profit generation. Specifically, the capability to forecast the transition to the Tornado would give a firm a significant advantage. Research has shown that there is a form of path dependence where by the dominant firm is propelled to market dominance through a series of self-reinforcing loops. The ability to take an early market lead as the Tornado begins could ensure that your product would be the ultimate market leader.

Forecasting inflection points would also give firms the ability to execute better financial planning. Many firms are uncertain about when money should be spent and how to properly invest in their product. An assumption that the product is out of the chasm, or that a chasm does not exist prompts aggressive infrastructure investment. This could easily lead to bankruptcy should the chasm exist or be prolonged as firms exhaust their capital reserve. Forecasting of inflection points would give visibility into how to develop spending plans that enable firm solvency.

Fundamental Technology Life Cycles

While the preceding research has addressed primarily product life cycles associated with high technology products, an even greater opportunity exists for analyzing the underlying fundamental technologies. For example, while the current research would allow analysis of a DVD player, a more powerful analysis would be to determine the life cycle phases of red laser, blue laser and ion beam technologies. It is believed that this would be possible by analyzing the rate of patent filings for a given technology. Preliminary research indicates that patent introductions for a given technology follow a curve closely resembling the technology adoption life cycle presented earlier. By turning the analysis to the underlying technologies, a better understanding of the true market drivers can be gained. Additionally, it will be much easier to predict the introduction of disruptive technologies.

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