Hard-disk maker 1973-93 *overshoot rooted in disruptive innovation*

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Abstract

Model analysis in system dynamics (SD) entails articulating exactly how the structure of circular, feedback relations among variables in a system determines its performance through time. This article combines disruptive innovation (DI) theory with SD to show the use and benefits of model analysis with the pathway participation metric (PPM), implemented in the *Digest*® software. The model replicates the hard-disk makers' overshoot and collapse dynamics that DI allegedly caused. Multiple insights emerge from the dynamics the model computes. Model analysis shows that, over five distinct time phases, four different feedback loops become most prominent in generating the hard-disk makers' population dynamics from 1973 to 1993. And *Digest*® helps detect exactly how changes in loop polarity and prominence determine system performance.

Keywords: adoption, Deming, disruptive, growth, innovation, system dynamics, technology

Disruptive innovation (DI) is becoming a mainstream strategy that firms use first to create and subsequently to sustain growth in many industries (Bower and Christensen 1995, Christensen 1997, Christensen, Johnson and Dann 2002, Christensen and Raynor 2003). Honda's small off-road motorcycles of the 60s, for example, Apple's computers and Intuit's accounting software initially under-performed established product offers. But these innovations brought new value propositions to new market contexts that did not need all the performance incumbents offered. They created massive growth through "creative creation" (Zhang 2001), as opposed to "creative destruction" (Schumpeter 1934). After rooting themselves in a simple application, disruptive innovations improve inescapably until they "change the game" (Gharajedaghi 1999), driving previously market-share dominant firms to the sidelines.

Typically, DI firms employ discontinuity in technological and business innovations as opposed to the sustaining, competency-enhancing innovations that drive improvements to existing technologies and revenue streams, which established industry players enjoy. Christensen and Raynor (2003) see DI not as the product of random events, but as a repeatable process that firms can design and replicate with sufficient regularity and success, given an adequate understanding of the circumstances associated with the genesis and distinct dynamics such strategies entail. Similarly, Christensen et al (2002, p. 42) urge managers adept in developing new business processes to design robust, replicable DI processes for creating and nurturing new growth business areas. In so doing, they must (a) seek a balance between resources that sustain short-term profit and investments in high-growth opportunities and (b) use both separate screening processes and separate criteria for judging sustaining and disruptive innovation projects. Yet, disruptive innovation strategies increase the odds of successful growth from six to 37 percent per year (Christensen 1997).

DI refers to highly revolutionary or discontinuous innovations that let customers embrace new paradigms. While it is becoming widely popular and DI authors describe its multifaceted and interrelated issues, this article adds a unique insight to Christensen's (1992) own initial understanding of the effects DI had on the hard-disk makers' overshoot and collapse. Which might help managers design and implement disruptive innovation as a competitive strategy.

Namely the article replicates Christensen's (1992) hard-disk makers' overshoot and collapse data with the help of a system dynamics (SD) model. The model draws on archetypal SD overshoot and collapse work (Alfeld and Graham 1974, Mojtahedzadeh, Andersen and Richardson 2004), which covers models in many areas with similarities in the structure of causal processes. Indeed, at the right level of abstraction, SD researchers encounter similar causal mechanisms that underlie seemingly highly diverse phenomena (Forrester 1961).

Client-driven, the entire system dynamics (SD) modeling process aims at helping managers articulate exactly how the structure of circular feedback relations among variables in a system they manage determines its performance through time (Forrester and Senge 1980). In the endless hunt for superior organizational performance, which only 'systemic leverage' endows (Georgantzas and Ritchie-Dunham 2003), SD brings its basic tenet: the structure of feedback loop relations in a system gives rise to its dynamics (Meadows 1989, Sterman 2000, p. 16).

Both as an inquiry field and as a coherent problem-solving method, SD can attain its spectacular Darwinian sweep (Atkinson 2004) as long as it formally links system structure and performance. To help academics and practitioners see exactly what part of system structure affects performance through time, i.e., detect shifting loop polarity and dominance (Richardson 1995), SD researchers use tools from discrete mathematics and graph theory first to simplify and then to automate model analysis (Gonçalves, Lerpattarapong and Hines 2000, Kampmann 1996, Mojtahedzadeh 1996, Mojtahedzadeh et al 2004, Oliva 2004, Oliva and Mojtahedzadeh 2004). Mostly, they build on Nathan Forrester's (1983) idea to link loop strength to system eigenvalues.

Cast as a methodological application, this article shows the use and benefits of model analysis with Mojtahedzadeh's (1996) pathway participation metric (PPM) implemented in his Digest® software (Mojtahedzadeh et al 2004). Shown here is a small part of a modeling project that combined disruptive innovation theory with SD to answer specific client concerns about the dynamic consequences of designing implementing DI strategies in established high-technology markets that contain over- and under-served customers (Schade 2005).

By definition, disruptive innovation is a dynamic process. Any model that purports to explain the evolution of a dynamic process also defines a dynamic system either explicitly or implicitly (Repenning 2002). A crucial aspect of model building in any domain is that any claim a model makes about the nature and structure of relations among variables in a system must follow as a logical consequence of its assumptions about the system. And attaining logical consistency requires checking if the dynamic system the model defines can generate the real-life performance of the dynamic process the model tries to explain.

But most existing DI models are merely textual and diagrammatic in nature. Given a particular disruptive innovation situation, in order to determine if a prescribed DI idea can generate superior performance, which only 'systemic leverage' endows (Georgantzas and Ritchie-Dunham 2003), managers must mentally solve a complex system of difference or differential equations. Alas, relying on intuition for testing logical consistency in dynamic business processes might contrast sharply with the long-certified human cognitive limits (Morecroft 1985, Paich and Sterman 1993, Sterman 1989); limits that even seasoned researchers who try to understand the dynamic implications of their own models often fail to overcome (Repenning 2002, Sastry 1997).

Aware of these limits, the article makes two contributions. *One* is the culmination of the early disruptive innovation literature into a generic model of the hard-disk makers' overshoot and collapse. Using a generic structure from prior SD overshoot and collapse work, the model contains assumptions common to seemingly diverse theories in economics, epidemiology, marketing and sociology. *Two* is the translation of these seemingly diverse components into a computer simulation environment that allows addressing the specific concerns of a real-life client by generating the overshoot and collapse dynamics of the hard-disk makers' population. Both contributions stem from articulating exactly how elements common to generic SD structures interact through time. Client-driven, the entire SD modeling process aims at helping managers articulate exactly how the structure of circular feedback relations among variables in the system they manage determines its performance through time (Forrester and Senge 1980).

Multiple new insights emerge from the dynamics the model presented here computes. Model analysis shows that, over five distinct time phases, four different feedback loops become most prominent in generating the hard-disk makers' population dynamics from 1973 to 1993.

Following a brief a review of the disruptive innovation literature below, the article proceeds with model description. The results section follows the same progression as model description does but, using *Digest*®, also looks at the model's shifting loop polarity and prominence. The article does not merely translate Christensen's (1992) work into a SD model to replicate his results. It dares to ask *how* and *why* the model produces the results it does. With the help of *Digest*®, the article ventures beyond *dynamic* and *operational thinking*, seeks insight from system structure and thereby accelerates *circular causality thinking* (Richmond 1993). *Digest*® helps detect exactly how changes in loop prominence determine system performance.

Background research

Innovation ranges from evolutionary to revolutionary (Christensen, 1997; Hill and Jones 1998, Trott 2001, Veryzer, 1998). Evolutionary innovation is critical to sustaining mainstream markets (Baden-Fuller and Pitt 1996, Hall and Vredenburg 2003, Hill and Jones 1998). But revolutionary breakthroughs lie at the core of wealth creation (Schumpeter 1934). By definition, revolutionary innovations serve as the basis for future technologies, goods, services and industries (Christensen 1997, Christensen and Rosenbloom, 1995, Hamel 2000, Tushman and Anderson 1986). And DI is extremely important to specialized regional economies because of the radical and fundamental changes it brings (Zhang 2001).

The main difference between DI and a sustaining strategy is based on the circumstances or context of innovation:

> In sustaining circumstances—when the race entails making better products that can be sold for more money to attractive customers—we found that incumbents almost always prevail. In disruptive circumstances—when the challenge is to commercialize a simpler, more convenient product that sells for less money and appeals to a new or unattractive customer set—the entrants are likely to beat the incumbents. This is the phenomenon that so frequently defeats successful companies. It implies, of course, that the best way for upstarts to attack established competitors is to disrupt them (Christensen and Raynor 2003, p. 32).

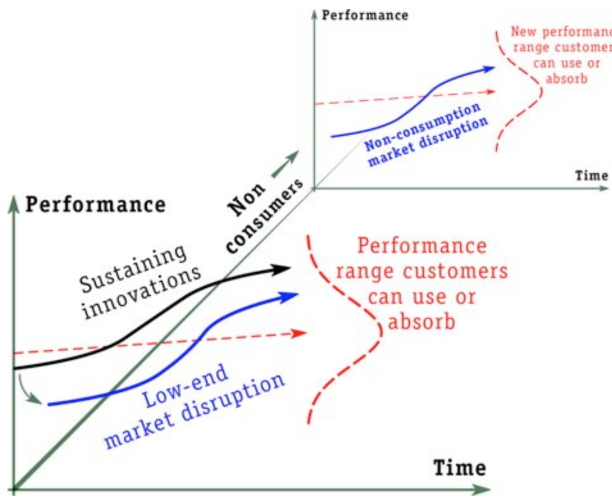
In order to be successful at launching and growing a disruptive model, a business needs to become aligned with the disruptive context in all its critical aspects: vision, decision making, business processes and cost structure. Once the alignment is in place to translate ambiguity, complexity and uncertainty into information adequacy (Veryzer 1998), growth tends to follow a specific pathway to superior performance (Thomond and Lettice 2002).

Typically, disrupters start out small and operate for some time on the fringes of existing markets, growing and establishing a foothold under the incumbents' radar screens. At the heart of an innovation with the potential to disrupt a mature industry, perhaps even to overtake and to displace incumbent firms through time, is a technology and a product or service platform that marks a departure from incremental improvement in the form of product extensions and add-ons to existing goods and services (Hall and Vredenburg 2003). Such a technology fills a previously unidentified or unaddressed niche with a value proposition aligned with the situations customers find themselves in, with needs, or 'jobs to do' in the DI literature, arising from their peculiar circumstances (Christensen and Raynor 2003, Thomond and Lettice 2002, Ulwick 2002).

A disrupter firm offers new choices in the form of stripped down functionality at a lower price or 'less for less'. Adapted from Christensen and Raynor (2003, p. 44) and Thomond and Lettice (2002), Fig. 1 shows the low-end and non-consumption markets disrupters exploit. The sustaining innovations of established firms often over-supply customers with technological functionality or services that customers do not actually need. The straight broken lines of Fig. 1 show the trajectories of increasing customer requirements for a given good or service. The sustaining innovations solid line on the front panel of Fig. 1 is the increasing performance the good or service offers, which is steeper than the customer requirements broken line. For example, mainframe and mini-computers in the late 1980s offered customers higher levels of performance, features and capability than they could use. This oversupply left a vacuum at the low-end of the market for a 'simpler' product offering: the personal computer (PC).

When introduced, along the solid, low-end disruption line on Fig. 1, PCs offered lower performance to customers and users that mainstream mainframe/mini-computers did. But a niche of consumers valued PCs and, through time, their technological performance improved along the trajectory of the low-end disruption line. At some point, PC performance equaled that demanded by the average mainstream customers of mainframes/mini-computers. So they started to switch, causing a widespread disruption of the established mainframe/mini-computer market and driving many incumbent firms out of business. Depending on the performance ranges customers can use or absorb to get a job done, new goods and services continually improve, usually faster than the average customer's requirements, leaving space for new-market disruption waves among non-consumers on the back panel of Fig. 1. Potentially, for example, the fast evolving personal digital assistant (PDA) and Apple's i-Pod might next disrupt the PC market further in the future.

Figure 1 The low-end and non-consumption markets DI firms exploit (adapted from Christensen and Raynor 2003, p. 44, and Thomond and Lettice 2002)

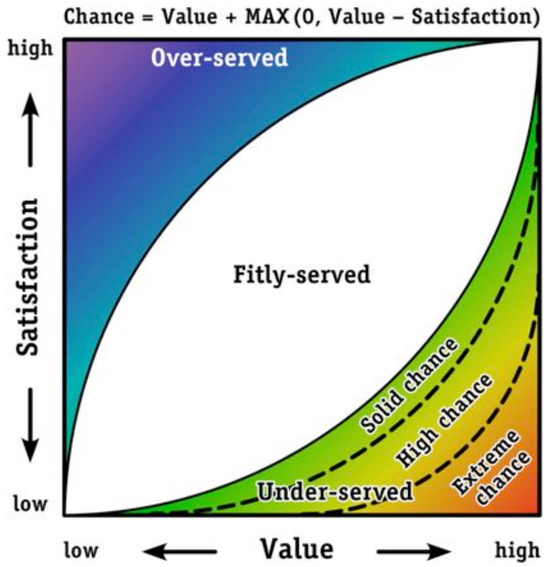


DI firms target market segments currently unable to purchase a good or service or to fill a specific need for lack of appropriate infrastructure or a specific set of skills. Or because the price points at which the good or service is available are above what that segment of the population can afford. In effect, disrupter firms targeting non-consumption are creating new markets by addressing the needs of existing non-consumers. Each firm exploits its ability to appeal to incumbent firms' low-end markets, i.e., over- and under-served customers facing a good or a service with functionality that far exceeds their needs; at a price they only pay reluctantly for lack of alternatives. Contrary to those fitly served, customers in such market segments cannot absorb sustaining performance improvements that exceed the range of utility they need or know how to exploit (Fig. 2).

Once a DI firm becomes successful at penetrating the non-consumption and low-end tiers, and has been on the market enough time to improve service delivery, to strengthen core business processes and to achieve a reasonable level of profitability, the business is poised for the next step: an up-market march that entails going after incumbent firms' higher end segments with an improved or expanded product/service offering and enhanced functionality at higher price points. The disrupter must be aware that moving up market to contest an incumbent's lock-in of lucrative customers might trigger a wave of retaliation. So disrupters must ensure sufficient readiness to address the competitive response prior to embarking on their up-market march.

In competitive dynamics terms, disrupters exploit what Christensen and Raynor (2003, p. 35) call "asymmetric motivation", namely incumbents' exclusive focus on investing in sustaining innovations and improved presence in the high-end, most profitable market segments. As they pay very little attention to new and lower-end markets, they allow disruptive entrants to move in under the radar, positioning themselves to eventually move up-market and to begin carving paths into the very markets established players are busy defending.

Figure 2 Customer value-satisfaction phase space where firms identify and prioritize DI chances, i.e., jobs and outcomes that over- and under-served customers value (adapted from Schade 2005, p. 19)



Business wise, the critical ingredient to penetrating a disruptive market niche is having the technological and commercial means to tailor a good or service as closely as possible to the circumstances or jobs to do customers find themselves in and to recognize the opportunity in the first place. Innovations that combine commercial and technological discontinuities are most attractive from a disruptive potential perspective. Compact disks and jump drives are good disruptive growth examples. Not only are they technologically capable, but also rank high on Veryzer's (1998) perceived product (good or service) performance dimension. Despite the high environmental turbulence, market risk and uncertainty, being in a market that blends commercial and technological competence discontinuity suggests ample opportunity for disruptive growth.

Firms that know how to harness technological competence discontinuity to create commercial discontinuities grow by opening up new market niches. A disrupter's successful venture into uncharted territory with a real value proposition causes a shift in incumbents' perception of established competitive dynamics. Dawning awareness of the nature and magnitude of the disruptive threat does, however, little to relieve the profit motive that keeps traditional players' short-term fortunes wedded to the satisfaction of their most demanding and profitable customers in the higher tiers of the market, even if that opens the door for migration to existing and new competitors in the lower market tiers. Even after they see a shift in the basis of competition for their industry and grasp the wider implications for long-term growth and perhaps for the very survival of their business, established players get caught in a bind.

Hard pressed to maintain short-term profitability by pouring resources into defending their high-end market presence, incumbents begin to compromise long-term growth by allowing disrupters to eat into the lower-end segments and undermine their competitive posture without as much as lifting a finger in the initial stages of disruption. Incumbents face a cost disadvantage compared to disrupters' typically light cost structure. This limits when and how incumbents can respond to the threat. Taking a longer-term view may well suggest retaliating early and with great force. Disrupters are typically ideally positioned to take advantage of the time lag to retaliation by strengthening their presence and improving the quality of their offering and its overall value proposition as they prepare to embark upon an up-market march. A successful up-market march can spell a prolonged period of upset and transformation for entire industries as old ways of doing business and serving customers give way to superior ways of addressing customer needs or jobs to do, at a more granular level and at a lower price.

Mojtahedzadeh's *Digest*® software plays a crucial role in the analysis of the article's model. The pathway participation metric inside *Digest*® detects and displays prominent causal paths and loop structures by computing each selected variable's dynamics from its slope and curvature, i.e., its first and second time derivatives. Without computer simulation, even experienced modelers find it hard to test their intuition about the connection between circular causality and SD (Oliva 2004, Mojtahedzadeh *et al* 2004). Using *Digest*® is, however, a necessary but insufficient condition for insight. The canon? Insightful articulations that link performance to system structure demand integrating insight from dynamic, operational and feedback loop thinking (Mojtahedzadeh *et al* 2004, Richmond 1993).

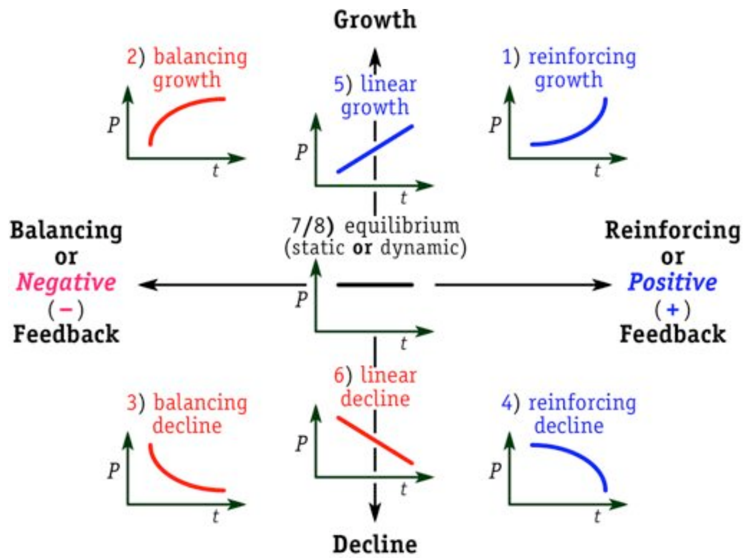
Linked to eigenvalue and dominant loop research, Mojtahedzadeh's (1996) pathway participation metric is most promising in formally linking performance to system structure. Mojtahedzadeh *et al* (2004) give an extensive overview of PPM that shows its conceptual underpinnings and mathematical definition, exactly how it relates to system eigenvalues and concrete examples to illustrate its merits. Very briefly, PPM sees a model's individual causal links or paths among variables as the basic building blocks of structure. PPM can identify dominant loops, but does not start with them as its basic building blocks. Using a recursive heuristic approach, PPM detects compact structures of chief causal paths and loops that contribute the most to the performance of a selected variable through time.

Mojtahedzadeh *et al* (2004, pp. 7-11) also present *Digest*®, the software that enables the *painless* use of the PPM *algo*rithm for model analysis. Most caringly, the software use and its outputs consume about five pages of their article. So, briefly again, *Digest*® detects the causal paths that contribute the most to generating the dynamics a selected variable shows. It first slices a selected variable's time path or trajectory into discrete phases, corresponding to eight behavior patterns through time (Fig. 3). Once the selected variable's time trajectory is cut into phases, PPM decides which pathway is most prominent in generating that variable's performance within each phase. As causal paths combine to form loops, combinations of such circular paths shape the most influential or prominent loops within each phase.

Mojtahedzadeh et al (2004) conclude with research directions *vis-à-vis* combining multiple loops, which drive performance within a single performance phase, for added insight into the dynamic trajectory of a single variable and merging multi-variable analyses into a coherent articulation of exactly how system structure drives overall system performance. They are also concerned whether model analysis imparts useful insights to clients' real-life performance challenges and if both academics and practitioners will understand the pathway participation metric enough to have faith in *Digest*®.

In response to these concerns, Mojtahedzadeh is testing PPM with a multitude of classic SD models, such as, for example, Alfred and Graham's (1976) urban dynamics model (*cf* Mojtahedzadeh *et al* 2004). Similarly, Oliva and Mojtahedzadeh (2004) use *Digest*® to show that the shortest independent loop set (SILS), which Oliva (2004) structurally derived via an algorithm for model partition and automatic calibration, does contain the most influential or prominent causal paths that *Digest*® detects. This article contributes to this line of work.

Figure 3 Eight archetypal performance (P) dynamics (i.e., behavior patterns through time) might exist within a single phase of behavior for a single variable: (1) reinforcing growth, (2) balancing growth, (3) balancing decline, (4) reinforcing decline (5) linear growth, (6) linear decline and, last but not least, two kinds of equilibrium: either (7) static or (8) dynamic (adapted from Mojtahedzadeh et al 2004).



Model description

Extending DI with system dynamics hinges on two reasons. First, Deming's (2000) *System of Profound Knowledge*, which integrates systems, statistics, knowledge theory and psychology, begins with building appreciation for a system. Second, Deming said: “Until you draw a flow diagram, you do not understand you business” (*cf* Schultz 1994, p. 21). SD does use stock and flow diagrams to depict relations among variables in a system.

Hard-disk (HD) makers’ population and customer jobs to do sector

Figure 4 shows the model’s hard-disk (HD) makers’ population and customer jobs to do sector, reproduced from the simulation model built with *iThink*® (Richmond 2006). Table 1 shows the equations of the *iThink*® model. There is a one-to-one association between the model diagram of Fig. 4 and its equations (Table 1). Like the diagram on Fig. 4, the friendly algebra of Table 1 is also actual output from *iThink*®. Building a model entails first diagramming system structure on the glass of a computer screen and then specifying simple algebraic equations and parameter values. The software enforces consistency between model diagrams and equations, while its built-in functions help quantify parameters and variables pertinent to the hard-disk makers’ overshoot and collapse dynamics that disruptive innovation diffusion caused.

Rectangles represent stocks or level variables that accumulate in SD, such as the population of HD Makers (Fig. 4 and Eq. 1, Table 1). Emanating from cloud-like *sources* and ebbing into cloud-like *sinks*, the double-line, pipe-and-valve-like icons that fill and drain the stocks represent flows or rate variables that cause the stocks to change. The exit outflow of Fig. 4 and Eq. 5, for example, bleeds the HD Makers stock, initialized (INIT) with 18 hard-disk maker firms (Eq. 1.1, Table 1) per Christensen’s (1992) data. Single-line arrows represent information connectors, while circular icons depict auxiliary converters where constants, behavioral relations or decision points convert information into decisions.

Figure 4 Hard-disk (HD) maker population and user jobs-to-do model sector

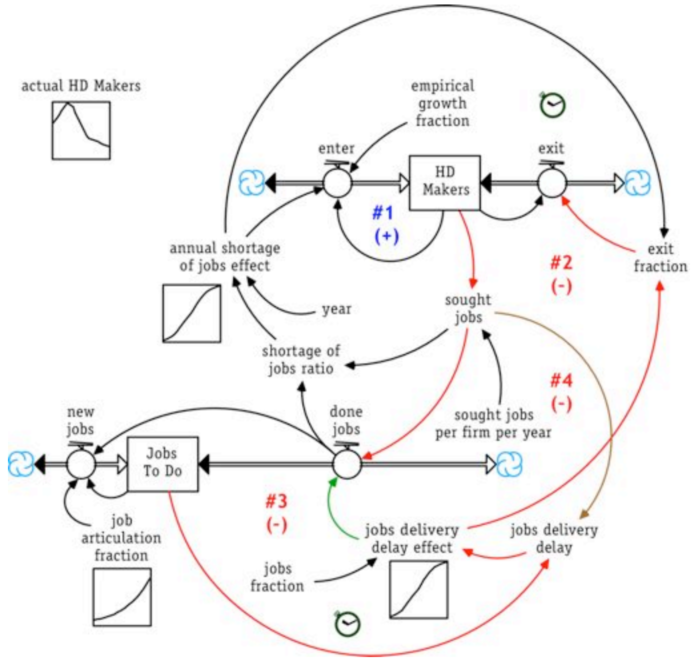


Table 1 Hard-disk (HD) makers' population and customers' jobs-to-do model sector equations

Stock or Level (State) Variable	({·} = comments and/or units)	*Equation #*
HD Makers(t) = HD Makers(t - dt) + (enter - exit) * dt		(1)
INIT HD Makers = 18 {unit: firm}		(1.1)
Jobs To Do(t) = Jobs To Do(t - dt) + (new jobs - done jobs) * dt		(2)
INIT Jobs To Do = TIME / job articulation fraction {unit: job}		(2.1)
Flows or Rate Variables		
done jobs = jobs delivery delay effect * sought jobs {unit: job / year}		(3)
enter = ROUND (STEP (HD Makers * empirical growth fraction * annual shortage of jobs effect, TIME)) {unit: firm / year}		(4)
exit = ROUND (STEP (HD Makers * exit fraction, TIME)) {unit: firm / year}		(5)
new jobs = 1 - job articulation fraction * (Jobs To Do - done jobs) / TIME {unit: job / year}		(6)
Auxiliary Parameters and Converter Variables		
empirical growth fraction = 0.1385 {unit: 1 / year}		(7)
exit fraction = (1.048 - jobs delivery delay effect * annual shortage of jobs effect) {unit: 1 / year}		(8)
jobs delivery delay = Jobs To Do / sought jobs {unit: year}		(9)
jobs fraction = 0.103 {unit: 1 / year}		(10)
jobs sought per firm per year = 29.3 {unit: job / firm / year}		(11)
shortage of jobs ratio = done jobs / sought jobs {unit: unitless}		(12)
sought jobs = HD Makers * jobs sought per firm per year {unit: job / year}		(13)
year = 1 {Data time interval (i.e., unit: year)}		(14)
actual HD Makers = GRAPH(TIME {Christensen's (1992) HD Makers data}) (1973, 18.0), (1974, 20.0), (1975, 22.0), (1976, 24.0), (1977, 26.0), (1978, 28.0), (1979, 27.0), (1980, 26.0), (1981, 23.0), (1982, 20.0), (1983, 17.0), (1984, 14.0), (1985, 11.0), (1986, 10.4), (1987, 9.75), (1988, 9.12), (1989, 8.50), (1990, 7.88), (1991, 7.25), (1992, 6.62), (1993, 6.00)		(15)
annual shortage of jobs effect = GRAPH(shortage of jobs ratio / year {unit: 1 / year}) (0.00, 0.00), (0.1, 0.06), (0.2, 0.14), (0.3, 0.255), (0.4, 0.395), (0.5, 0.535), (0.6, 0.685), (0.7, 0.825), (0.8, 0.92), (0.9, 0.98), (1, 1.00)		(16)
jobs delivery delay effect = GRAPH(jobs fraction * jobs delivery delay {unit: unitless}) (0.00, 0.00), (0.1, 0.06), (0.2, 0.14), (0.3, 0.255), (0.4, 0.395), (0.5, 0.535), (0.6, 0.685), (0.7, 0.825), (0.8, 0.92), (0.9, 0.98), (1, 1.00)		(17)
job articulation fraction = GRAPH(TIME {unit: 1 / year}) (1973, 0.197), (1974, 0.221), (1975, 0.237), (1976, 0.259), (1977, 0.287), (1978, 0.325), (1979, 0.369), (1980, 0.416), (1981, 0.468), (1982, 0.527), (1984, 0.593), (1985, 0.667), (1986, 0.75), (1987, 0.844), (1988, 0.949), (1989, 1.07), (1990, 1.20), (1991, 1.35), (1992, 1.52), (1993, 1.71)		(18)

The enter inflow (Eq. 4), which fills the HD Makers stock, depends, for example, on the HD Makers population itself, multiplied by the industry's empirical growth fraction, an exogenous auxiliary constant parameter (Eq. 7), and by the annual shortage of jobs effect (Eq. 16), a graphical table function.

SD knowledge ecology begins by differentiating stocks from flows and how stocks and other variables and parameters determine the flows. Identifying the integration points facilitates understating one source of dynamic behavior in the system. The stock and flow diagram on Fig. 4 shows accumulations and flows essential in generating the performance dynamics of the hard-disk maker population, the fate of which the disruptive innovation diffusion process determined (Christensen 1992). This diagram also tells, with the help of the equations on Tables 1, what drives the flows in the system. In the context of systems thinking (ST), stock and flow diagrams like the one on Fig. 4 help accelerate what Richmond (1993) calls *operational thinking*.

The model on Fig. 4 and Table 1 is based on a classic structure that illustrates how the population of firms in a particular industry grows through time until the resources needed to support its growth are depleted (Alfeld and Graham 1974, Mojtahedzadeh et al 2004). The model captures real-world processes as feedback loops that might cause the performance dynamics of its pertinent variables. Caught in a web of eleven feedback loops, the HD Makers' population, for example, grows when, *ceteris paribus*, new hard-disk makers enter through a reinforcing or positive (+) loop and declines when, again ceteris paribus, they exit through a balancing or negative (–) loop (Fig. 4). Once new firms join the hard-disk makers' population, they immediately begin to deplete the customers' Jobs To Do stock (Eq. 2), a vital resource for HD Makers to stay in business.

The shortage of jobs ratio (Eq. 12), i.e., the ratio of done jobs (Eq. 3) to sought jobs (Eq. 13), also affects new firm entry and exit indirectly. Last but not least, the customers' Jobs To Do stock controls its own depletion rate (i.e., done jobs) by modulating the jobs delivery delay (Eq. 12), i.e., the ratio of Jobs To Do to sought jobs (Eq. 13).

Given its specific set of parameters and initial values, to explain the dynamics the model generates, the question is which of the eleven feedback loops HD Makers are caught in are most influential or prominent in generating the HD Makers' behavior Christensen (1992) observed. For example, what made the customers' Jobs To Do decline rapidly? What drove HD Makers to grow rapidly in the first few years? What part of the structure is responsible for the decline of the hard-disk makers' population followed by its growth? Those familiar with this archetypal model structure might easily explain the growth and declining phases. It might not be as easy, however, to distinguish which part of the model contributes most to the dynamics of HD Makers in the transition from reinforcing (+) growth to a balancing (–) decline. Using *Digest*® allows detecting the most prominent or influential feedback loops as the HD Makers dynamics unfolds.

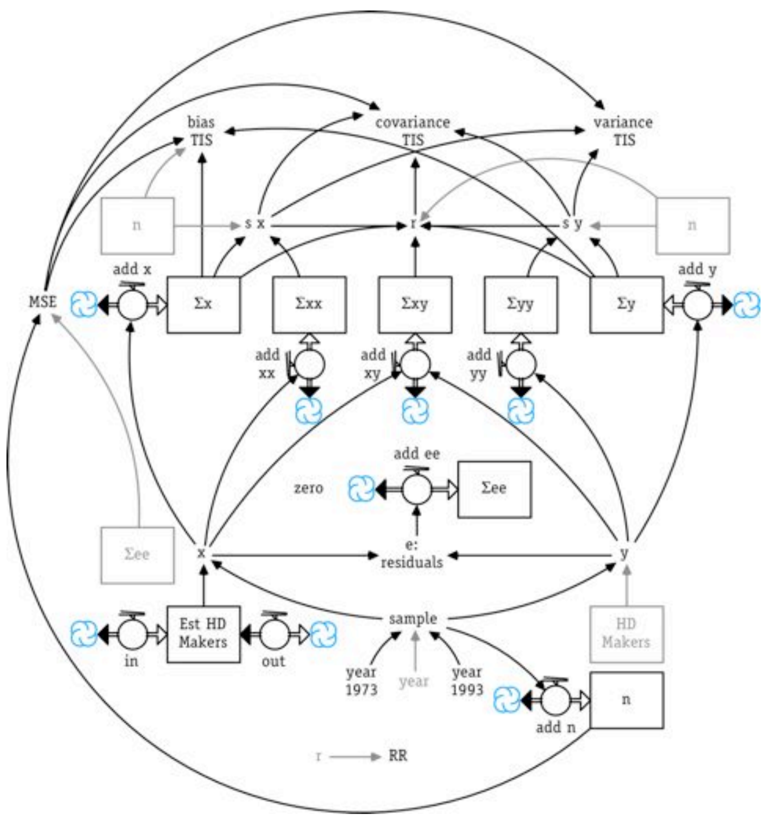
Behavior reproduction testing model sector

To replicate the DI-caused overshoot and collapse dynamics of the hard-disk makers' population that Christensen (1992) reports, the model's specific set of parameters and initial values were set to minimize the mean square error (MSE) between actual and simulation data. Computed on Fig. 5, Theil's (1966) inequality statistics (TIS) subsequently decompose MSE on Fig. 8.

TIS provide an elegant decomposition of the MSE into three components: bias (U^M), unequal variance (U^S) and unequal covariance (U^C), so that $U^M + U^S + U^C = 1$ (Oliva 1995, Sterman 1984 and 2000, Theil 1966). Briefly, bias arises when competing data have different means. Unequal variance implies that the variances of two time series differ. Unequal covariance means imperfectly correlated data that differ point by point. Dividing each component by the

MSE gives the MSE fraction due to bias (U^M), due to unequal variance (U^S) and due to unequal covariance (U^C). A large U^M reveals a potentially serious systematic error. U^S errors can be systematic too. When unequal variation dominates the MSE, the data match on average and are highly correlated but the variation in two time series around their common mean differs. One variable is a stretched out version of the other. U^S may be large either because of trend differences, or because the data have the same phasing but different amplitude fluctuations (Sterman 2000, p. 876). If most of the error is concentrated in unequal covariance, then the data means and trends match but individual data points differ point by point. When U^C is large, then most of the error is unsystematic and, according to Sterman: "a model should not be faulted for failing to match the random component of the data" (2000, p. 877).

Figure 5 Behavior reproduction testing model sector



Following this rather Laconic exposition, Fig. 5 shows the stock and flow diagram of the behavior reproduction testing model sector and Table 2 the sector's equations. Most of this sector is an implementation of Theil's (1966) (TIS), with explanatory comments included for each equation on Table 2. Worth noting, however, on Fig. 5 and Table 2 are the estimated hard-disk makers stock (Est HD Makers, Eq. 19), along with its associated in and out flows (Eqs 34 and 35). These last three model components help replicate Christensen's (1992) data exactly, with zero error, using the built-in *STEP* function of *iThink*®. This may seem like a futile exercise at the outset, but it helped convince the client of the much larger modeling project than what is shown here that replicating real-life data does not necessarily produce much insight, nor does it help one appreciate a dynamically complex system.

Table 2 Behavior reproduction testing model sector equations

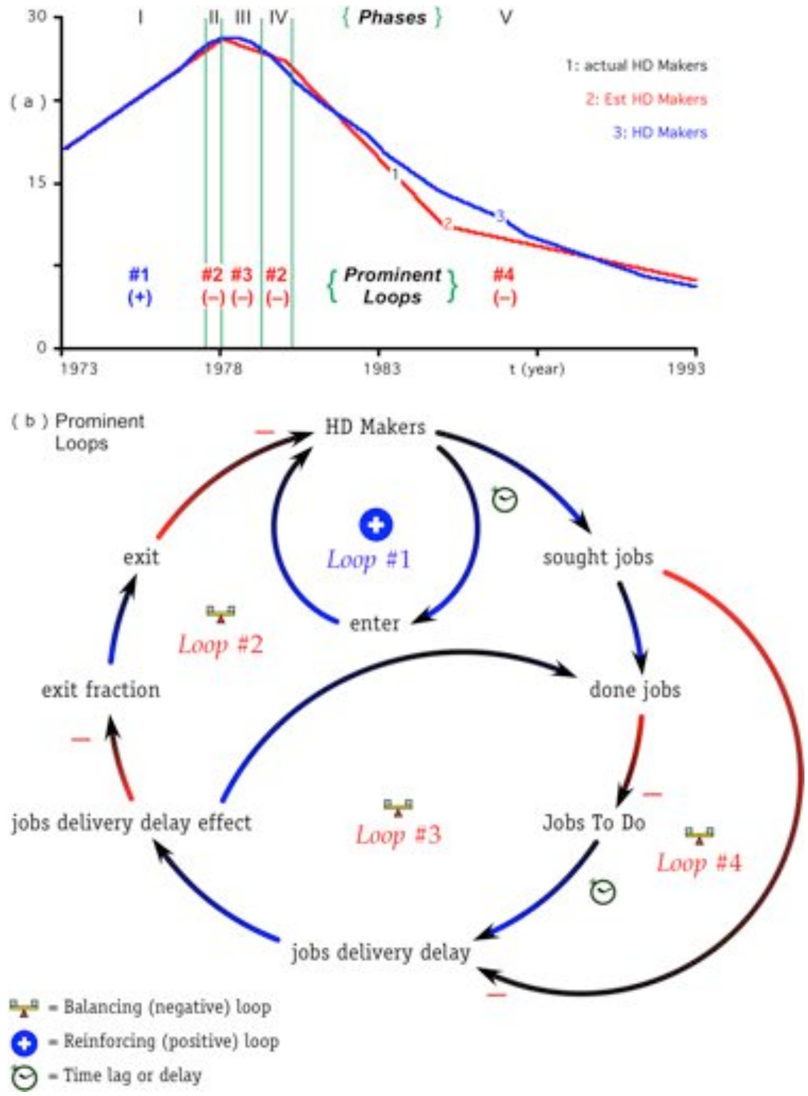
Stock or Level (State) Variable ({·} = comments and/or units)	*Equation #*
Est HD Makers(t) = Est HD Makers(t - dt) + (in - out) * dt; INIT Est HD Makers = 18 {unit: firm}	(19)
∑ee(t) = ∑ee(t - dt) + (add ee) * dt; INIT ∑ee = 0	(20)
∑x(t) = ∑x(t - dt) + (add x) * dt; INIT ∑x = 0 {Cumulative sum of the actual data}	(21)
∑xx(t) = ∑xx(t - dt) + (add xx) * dt; INIT ∑xx = 0 {Cumulative sum of the squared actual data}	(22)
∑xy(t) = ∑xy(t - dt) + (add xy) * dt; INIT ∑xy = 0 {Cumulative sum of the xy product}	(23)
∑y(t) = ∑y(t - dt) + (add y) * dt; INIT ∑y = 0 {Cumulative sum of the simulated data}	(24)
∑yy(t) = ∑yy(t - dt) + (add yy) * dt; INIT ∑yy = 0 {Cumulative sum of the squared simulated data}	(25)
n(t) = n(t - dt) + (add n) * dt; INIT n = 1e-9 {The current count n of data points}	(26)
Flows or Rate Variables	
add ee = e: residuals^2 / DT {Adds to the sum of squared errors between actual and simulated data}	(27)
add n = sample / DT {Increments n, i.e., adds one to the number of observations}	(28)
add x = x / DT {Adds to the cumulative sum of the actual data}	(29)
add xx = x^2 / DT {Adds to the sum of the squared actual data}	(30)
add xy = x * y / DT {Adds to the cumulative sum of the xy product of actual and simulated data}	(31)
add y = y / DT {Adds to the cumulative sum of the simulated data}	(32)
add yy = y^2 / DT {Adds to the cumulative sum of the squared simulated data}	(33)
in = STEP(2, 1973) - STEP(2, 1978) {unit: firm / year}	(34)
out = STEP(1, 1978) - STEP(1, 1980) + STEP(3, 1980) - STEP(3, 1985) + STEP(0.625, 1985) - STEP(0.625, 1993) {unit: firm / year}	(35)
Auxiliary Parameters and Converter Variables	
bias TIS = ((∑x / n) - (∑y / n))^2 / (1e-9 + MSE) {The unequal bias Theil inequality statistic (TIS) is the MSE fraction caused by unequal means of the actual and simulated data}	(36)
covariance TIS = (2 * s x * s y * (1 - r)) / (1e-9 + MSE) {The unequal covariance Theil inequality statistic (TIS) is the MSE fraction caused by imperfect correlation between actual and simulated data}	(37)
e: residuals = x - y {The difference between sampled actual and simulated data}	(38)
MSE = ∑ee / n {The mean squared error between actual and simulated data}	(39)
r = ((∑xy / n) - (∑x / n) * (∑y / n)) / (s x * s y + 1e-9) {The correlation between x and y}	(40)
RR = r^2 {The coefficient of determination R^2 is the square of the correlation coefficient}	(41)
s x = SQRT ((∑xx / n) - (∑x / n)^2) {The standard deviation of x}	(42)
s y = SQRT ((∑yy / n) - (∑y / n)^2) {The standard deviation of y}	(43)
sample = PULSE (DT, year 1973, year) * (STEP (1, year 1973) - STEP (1, year 1993 + DT / 2)) {Sterman (2000, Ch. 21 + CD) suggests sampling once a year between in order to compare actual and simulation data only where actual data exist}	(44)
variance TIS = (s x - s y)^2 / (1e-9 + MSE) {The unequal variance Theil inequality statistic (TIS) is the MSE fraction caused by the unequal variance of actual and simulated data}	(45)
x = sample * Est HD Makers {The actual data sampled}	(46)
y = sample * HD Makers {The simulated data sampled}	(47)
year 1973 = 1973 {The data start time}	(48)
year 1993 = 1993 {The data end time}	(49)
zero = 0 {This plots a horizontal line at the origin of the y axis in the time domain}	(50)

Simulation results

To be useful, model analysis must create insight via coherent explanations of how influential pieces of system structure give rise to performance through time. Figure 6 shows the simulation results for the hard-disk makers' population performance with time phases and prominent feedback loops. Clearly, the built-in *STEP* function of *iThink*® works wonders. The Est HD Makers behavior faithfully reproduces the actual HD Makers dynamics without error (Fig. 6a). But zero error in behavior pattern reproduction can also mean zero insight for appreciating a dynamically complex system. The HD Makers behavior (line #3 on Fig. 6a) provides a less impressive data fit, but the feedback loop web behind its dynamics is where insight lives.

The vertical lines on the time domain output of Fig. 6a show five distinct time phases in the HD Makers dynamics, which *Digest*® identified by detecting behavior pattern shifts. Phase I of the HD Makers dynamics on Fig. 6a shows reinforcing growth (Fig. 3), which lasts for about 4 years. During this time, both the slope (first time derivative) and the curvature (second time derivative) of the variable of interest, HD Makers, remain positive. Also identified by *Digest*®, Phase II on Fig. 6a shows balancing growth. The slope and curvature of HD Makers have opposite signs in this phase. Phases III and IV show reinforcing decline. And lastly, in its fifth distinct phase (Fig. 6a) the HD Makers dynamics shows balancing decline (Fig. 3).

Figure 6 Simulation results with time phases and prominent feedback loops



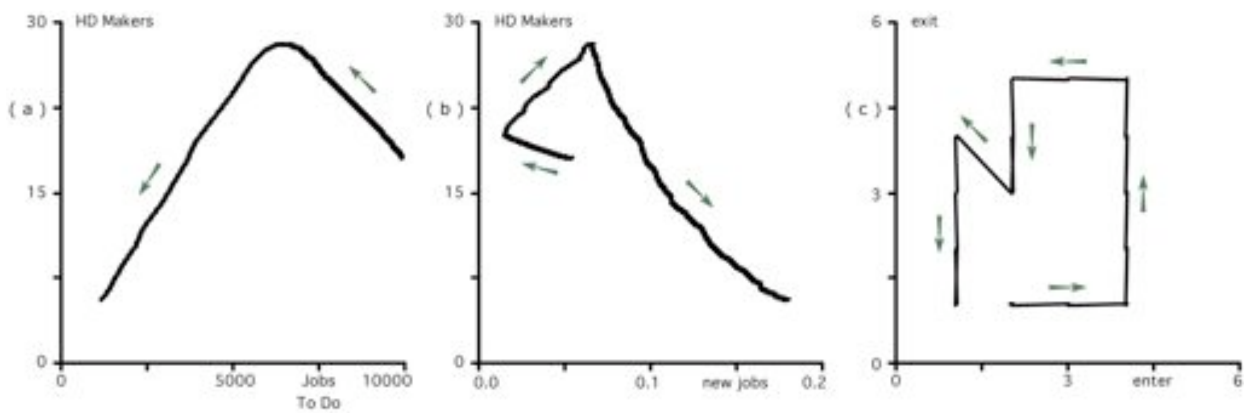
In addition to discerning distinct time phases in the dynamics of a variable of interest, *Digest*® also detects and displays the most influential or prominent structures that contribute the most to the selected behavior pattern in each phase. Corresponding to the first phase of the behavior of HD Makers is reinforcing feedback loop #1 of Fig. 6b which, according to *Digest*®, is the most prominent loop in generating the reinforcing growth in the hard-disk makers' population. Initially, HD Makers attract new hard-disk makers to enter the industry, thereby increasing HD Makers further. By inspecting the model structure on Fig. 4, one could identify eleven feedback loops surrounding HD Makers. Using its pathway participation metric, *Digest*® automatically selects reinforcing feedback loop #1 as the most prominent structure among all the other loops in the model.

In phase II of the HD Makers dynamics, system control shifts from reinforcing loop #1 to the most influential structure or balancing feedback loop #2 of Fig. 6b, associated with the customers' Jobs To Do stock. Initially plenty in phase I, customers' Jobs To Do now begin to fall, along the pathway that carries the effect of balancing loop #2 to HD Makers. This same structure is also most prominent in phase IV of HD Makers' dynamics.

In phase III of the HD Makers behavior, balancing loop #3 becomes the most influential structure of Fig. 6b, associated with the customers' Jobs To Do stock and their delivery delay. Initially plenty in phase I, customers' articulated Jobs To Do now begin to fall, along the pathway that carries the effect of balancing loop #2 to HD Makers. By phase III, the large HD Makers population causes the done jobs rate to deplete the customers' articulated Jobs To Do faster. And as the more job delivery delay decreases because of the–by now–large hard-disk makers' population, the more it causes the exit fraction to increase, thereby forcing some HD Makers to exit, while preventing new ones from entry.

In phase IV, prominent loop #2 again takes over, now from loop #3, while keeping the customers' Jobs To Do stock in focus. In phase V, however, with HD Makers already dropping, prominent loop #4 bypasses the Jobs to Do stock, increasing the jobs delivery delay directly, indirectly causing the exit fraction, and thereby the exit rate of HD Makers, to slow down. According to *Digest*®, prominent loop #4 remain the most influential structure until the end of the simulation.

Figure 7 Phase plots of relations among pertinent variables



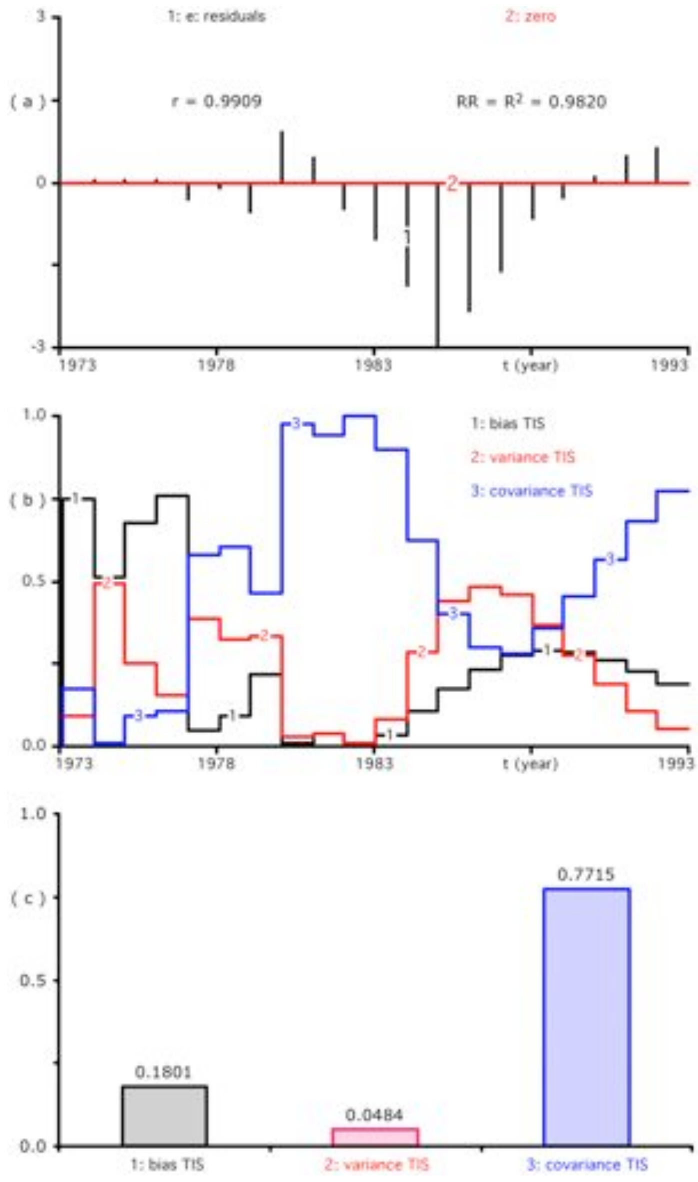
In phase II of Fig. 6, it may be easy to spot the role of the balancing feedback loop that controls the Jobs To Do stock depletion, when striving to explain why HD Makers is generating a balancing growth. The customers' articulated Jobs To Do is dropping, thereby preventing new hard-disk makers from entry. The subtlety in explaining the behavior of the HD Makers is the subsequent reinforcing decline in HD Makers' dynamics in phase IV. Some novices may even look for reinforcing feedback to explain the reinforcing decline. But *Digest*® tells that what forces HD Makers to fall faster and faster is exactly the same process that keeps their population at bay. Balancing loop #2, which controls Jobs To Do, prevents new hard-disk makers from entering and, once new entries fall behind those who exit, the HD Makers stock goes into reinforcing decline.

The relations among pertinent variables on the phase plots of Fig. 7 confirm the above arguments. In all three cases, their polarity changes, making it rather impossible to assess such relations with correlation statistics. On Fig. 7a, for example, as the customers' articulated Jobs To Do decline, HD Makers initially rise and subsequently fall. On Fig. 7b, new jobs gradually decrease as the HD Makes stock grows exponentially, then they begin to grow once the hard-disk makers' population slows down, i.e., begins to increase at a declining rate but, lastly, they increase even more rapidly once the HD Makes stock decreases.

Behavior reproduction test results

The coefficient of determination, R^2, which measures the variance in the data explained by the model as a dimensionless fraction, is a common statistics used to assess a model's ability to reproduce system behavior. The coefficient of determination is the square of the correlation coefficient, r, which measures the degree to which two series co-vary.

Figure 8 Behavior reproduction test results



Although widely reported because audiences expect it (Fig. 8), R^2 is actually not very useful. Two series with the same error can generate very different R^2 values depending on their trend (Sterman 2000, p. 874). Conversely, Theil's (1966) inequality statistics (TIS) use the mean square error (MSE), which measures the average error between competing data series in the same units as the variable itself and weights large errors more heavily than small ones.

Although both the r and the R^2 values are high on Fig. 8a, the residual plot shows an uneven pattern of serially autocorrelated errors. But Theil's inequality statistics (Fig. 8b and c) do support the model's usefulness. The unequal covariance TIS, U^C, dominates throughout the simulation (Fig. 8b), and Fig. 8c shows the end TIS values on a vertical bar graph. Most of the MSE fraction is concentrated above U^C, showing that the model captures the mean and trends in the actual data rather well, differing mostly point by point.

Concluding remarks

Nothing is random in life. In business processes and systems, "randomness is a measure of our ignorance" (Sterman 2000, p. 127). Georgantzas and Orsini (2003) concur, while Hayes further elucidates: "Fretting about a dearth of randomness seems like worrying that humanity might use up its last reserves of ignorance" (Hayes 2001, p. 300). Christensen and Raynor (2003) might be right to see disruptive innovation as a repeatable process and not as the product of random events, but have the DI theory proponents used the right tools to help managers understand the circumstances associated with the genesis and distinct dynamics DI strategies entail?

Purely deterministic, this article's SD model is rather useful in explaining the HD Makers dynamics. It would be both premature and unproductive to draw broad generalizations based on this article's limited findings. With four different feedback loops becoming prominent along five distinct phases, however, it is rather difficult to imagine how DI proponents try to explain the hard-disk makers' rise and fall between 1973 and 1993 without the help of SD.

It is Mojtahedzadeh's *Digest*®, with its analysis of shifting prominent structure and polarity phases that has helped reveal the above model analysis results. *Digest*® offers a novel mode for understanding and explaining what would normally require dominant loop (Richardson 1995) and eigenvalue analyses (Forrester 1983). Qualitatively, using Mojtahedzadeh's (1996) pathway participation metric implemented in *Digest*® feels much akin to simulation than to eigenvalue analysis. Armed with PPM, however, *Digest*® delivers results equivalent in rigor to eigenvalue analysis, but with the finesse of computer simulation.

Indeed, graph theory tools ala PPM can help make sense of the dynamic and structural complexity of SD models, even if Oliva (2004, p. 331) finds SD keen in understanding system performance, "not structure *per se*", in lieu of its core tenet that system structure causes performance. Undeniably, while looking for *systemic leverage* in strategy making (Georgantzas and Ritchie-Dunham 2003), modelers do play with structural changes for superior performance in business and civil litigation. Having model analysis tools such as *Digest*® helps articulate structural complexity and thereby enables both effective and efficient strategy designs.

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