The Intelligent Future

By Noel P. Greis, Jack G. Olin, and John D. Kasarda

How do you succeed in an environment of increasingly complex supply chain processes and unrelenting demands for real-time response and control? The answer may come in the form of intelligent machine agents that can observe their environment, interpret information, make decisions, and even initiate actions—the *right* actions. This intelligent future may not be that far off. And the early adopters of the technology that makes it happen stand to gain a huge first-mover advantage.

The recent revolution in Internet-based information technologies is being followed by an equally dramatic revolution in decision support in the form of intelligent software—or "machine agents." Intelligent agents are able to generate, process, store, filter, correlate, broadcast, and route information for real-time, event-driven coordination and decision making across today's global enterprise. These new technologies can interpret massive and complex amounts of information, uncovering patterns undetectable even to the trained logistician, and then take action under supervised eyes. The notion of such software agents is compelling—and increasingly necessary—if we are ever to tame the growing complexity of the supply chain in the Internet age.

The complexity is further heightened by today's unforgiving, turbulent marketplace. Logistics and supply chain strategies demand end-to-end integration of the value chain, total asset visibility, and real-time control to respond to random and often unforeseen events. Reacting to these demands, managers are struggling to make their companies and extended enterprises more dynamically responsive—in short, to become real time and event driven. Event-driven companies gain competitive advantage by effectively marshaling real-time, active information to drive their business processes.[1]

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This article provides a first view of how these emerging new technologies—intelligent software or machine agents operating in an open information environment—can assist human agents in managing complex and interrelated logistics processes and transactions across the extended enterprise.

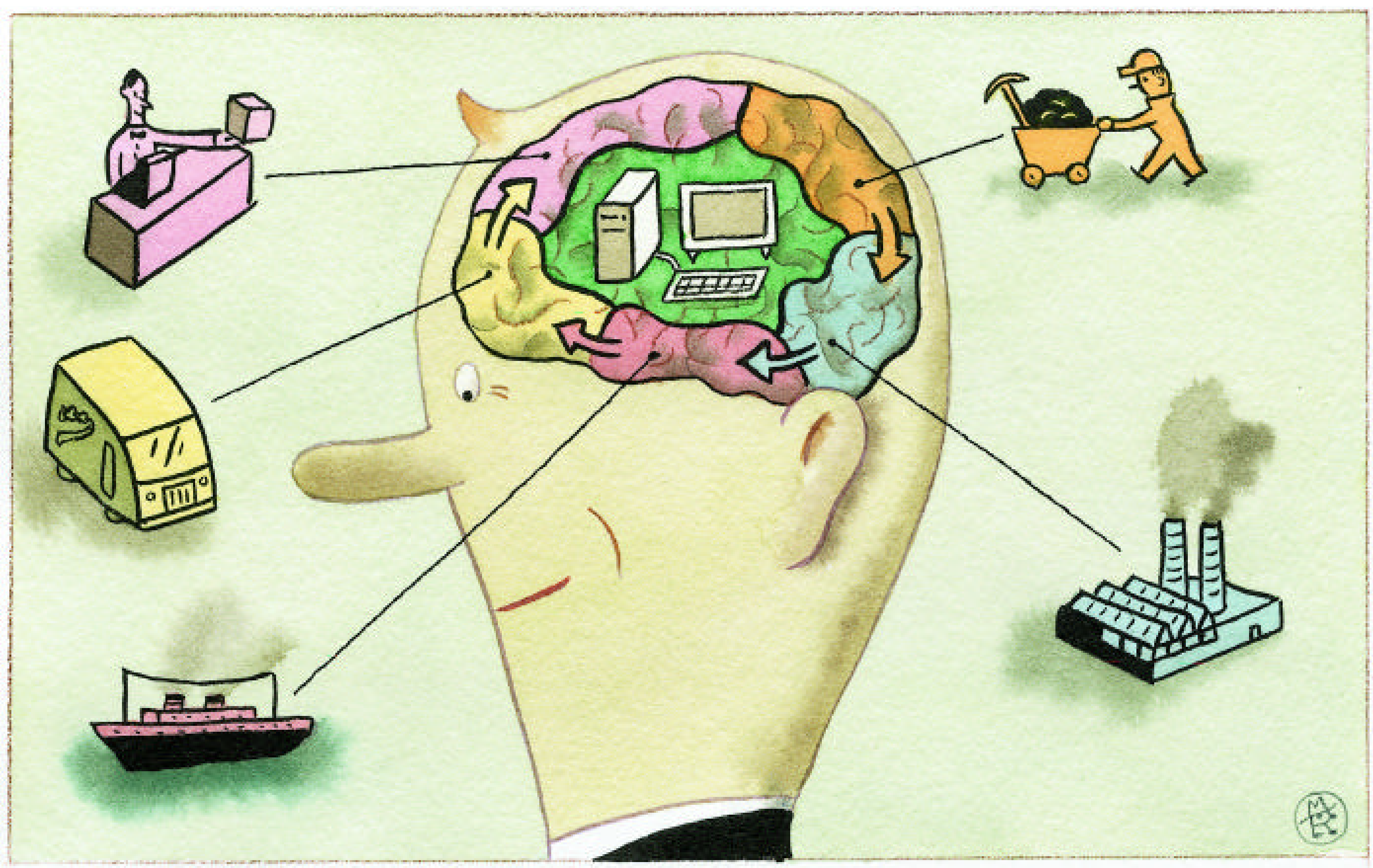
Just what are intelligent, or machine, agents? First, these agents are not—as we shall discuss later—to be confused with the artificial intelligence of the last few decades. Rather, agent technology represents a unique category of software that is defined through the specific functionality provided to the user by these software objects. Their primary functionality is in sensing the environment, processing information about the environment based on reasoning and/or interagent communication, and then acting on the environment. Unlike traditional user-initiated computer programs, machine agents can run continually in the background, ready to jump into action whenever the need arises. Primitive agents are already at work monitoring customer behavior on the Internet. Others control manufacturing operations in major U.S. automotive and aerospace companies.[2] As these agents mature and grow in capability, they will assume important new roles coordinating business processes across the extended global enterprise.

Intelligent logistics is defined as the application of machine agents to manage increasingly complex supply chain processes in the face of uncertainty and demands for real-time response and control. In intelligent systems, machine agents can respond automatically to changes in their environment, recover from disturbances, and even anticipate and prepare for change. Agents might be charged with monitoring inventory and transacting purchases. At a minimum, intelligent logistics can create and extend a competitive advantage in managing enterprise processes on a global scale. At its fullest, this technology has the potential to change everything from how products and services are defined and delivered to how companies interact with their customers.

Taming Complexity

The effects of the Internet on business have been pervasive and deep, altering not only the transactional process but also the relationship between customer and supplier. Customers around the world increasingly expect goods and materials to be delivered to their doorstep at nearly the same speed and ease with which they placed their order—in other words, at "click speed." This expectation of speed across the vast global marketplace is changing the calculus of logistics and supply chain management.

Companies now realize that they need a new generation of decision support to filter the rivers of information now available and then transform that information into constructive action. New Internet technologies offer the possibility of global connectivity across the extended enterprise in a fraction of a second. But they also engender higher expectations in customers around the world both for greater delivery speed



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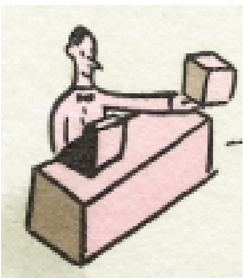
and for personalized goods and services that require complex coordination of activities across the supply chain. In short, we have created a digital dilemma where speed and complexity compete in the execution of a supply chain.

Many companies have turned to a set of tools referred to as "complexity science" to tame runaway complexity within their organizations and across the extended enterprise. Sparked by studies of natural systems, these problem-solving tools range from genetic algorithms and simulated annealing for general optimization problems to neural networks and intelligent software agents. Procter & Gamble, for example, has been exploring the use of complexity-based models to optimize purchasing decisions. The applications collect and analyze information from users about material availability and prices, and determine the best deals for purchases. By performing this analysis, the models can cut time and cost out of the company's supply chain.[3] The focus of intelligent software applications is not so much to predict and control the underlying process but rather to respond and adapt on the fly. Recently, for example, Southwest Airlines implemented a new cargo-routing strategy after experiencing bottlenecks at three of its airports. A detailed model of the cargo system, in which autonomous agents simulated all the elements of the system, revealed that the bottlenecks were due to too much loading and unloading of cargo at the major airports. This problem could be eliminated by letting the cargo fly on less direct routes.[4]



Intelligent logistics is the application of machine agents to managing the growing complexity of supply chain processes in the face of uncertainty and demands for real-time response and control.

Intelligent machine agents are key enablers of the event-driven, real-time, global enterprise because they support information processing and decision making by reducing the burden of complexity. The first requirement for such an enterprise is, of course, real-time availability and exchange of information. The emergence of the Internet, corporate intranets, and industry extranets have paved the way to such "open" communication within privacy and security constraints managed by firewall software. But even with the universal availability of information and the empowerment of supply chain managers that it enables, a severe barrier to real-time execution and action-initiation remains. The barrier is information overload and human limitations in filtering massive information and recognizing significant correlations and their implications.

For example, supply chain managers must track all information pertinent to any one event, recognize relationships across events, assess priorities, and define the best course of action immediately. When a production line is disrupted, managers must survey the suitability of alternative sites and suppliers worldwide and balance costs, distances, and forecasted demand. Humans can bring intuition, experience, and courage to these tasks. However, the large number of simultaneous, or at least parallel, decisions and transactions typical of a far-flung, complex enterprise would be well served by intelligent software agents. As we will describe, such agent-based systems can be programmed to observe their environment, reason about their observations, learn by observing their owners, negotiate with other agents, define alternative actions, and—if authorized by their human agent owner—even initiate action.

Machine agents, thus, represent a new category of software defined by their unique role in enterprise life—that of supporting and even acting on behalf of human agents. Their role is not to replace other software applications such as enterprise resource planning (ERP) software, network software, data management, or application program interface (API) software. Rather, they act as support agents to the humans who use these systems. As such, these agents would, of course, leverage all information and computational resources available to them. Their central role, however, is to sort through the jungle of information, processes, transactions, and internal and external events typically involved in the complicated day-by-day operations of today's complex, multinational companies.

In fact, many of these legacy software systems and applications are well suited for fusion with agent technologies. ERP systems, especially, are highly rigid to changes in the environment and transformations in fundamental business processes.[5] The overlay of agent networks to existing ERP systems could provide a cost-effective trajectory for many companies in pursuit of more adaptive and real-time business processes.

A Perspective on Machine Intelligence

Today's intelligent software is the result of more than half a century of thinking about "thinking." Alan Turing, an early proponent of computer intelligence, suggested in 1950 that a machine is intelligent if it cannot be distinguished from a human being during conversation.[6] In simple tests, subjects were seated in front of computers and engaged in dialogue with a "computer" without knowing whether a real computer or human was hidden behind the screen. A machine that successfully masqueraded as a human at least 50 percent of the time was deemed to be intelligent. An artificial intelligence movement evolved from this line of thinking. The machine was viewed as a substitute for a human brain and was capable of becoming an "expert" able to replace humans in certain tasks.

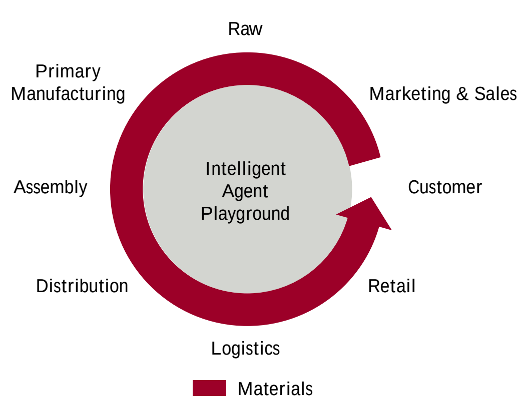
The intelligent agents of today must not be confused with the artificial intelligence of yesterday. Unlike the top-down approach of earlier generations, today's intelligent agent approach is to let intelligence develop from the bottom up—that is, distributed intelligence. Instead of a powerful mainframe computer directing activities across the enterprise, a network of agents can use local information to coordinate supply chain activities using the most up-to-date conditions.

In an agent-enabled intelligent environment, the multiple transactions and exchanges of information that drive material flow can be managed by software agents that maintain visibility across the network. These software agents notify affected parties of current or impending breakdowns in the supply chain and negotiate new arrangements. As shown in Exhibit 1, the transaction space between supply chain partners serves as an intelligent agent playground. Intelligent logistics, then, is the unleashing of software agents in an open information environment to observe, monitor, and initiate the transactions that control the movement of information, materials, and money across global supply networks. Agents make sure that information is shared, that documents are completed, and that goods and materials arrive and depart on time and at the proper location. In short, agents make sure that all the information that's needed, and only the information that's needed, is available to whoever needs it, when it's needed.

Consider a global automotive manufacturer like Ford or Toyota. Thousands of production and logistics operations scattered across the global supply and production network need to be synchronized to manufacture a particular vehicle. A multitude of various parts and components must be sequenced to arrive at the assembly line in an orchestrated fashion. In the past, production schedules were based on a planning cycle subject to periodic review. "Events," defined as exceptions such as production glitches or schedule changes, were difficult to trace and correlate across multiple sites. Changes in the assembly schedule could, at best, be dealt with in isolation within functional organizations. Correlated solutions across functional boundaries were difficult to identify and implement—and certainly not synchronized or even initiated in real time. A breakdown in a supplier's facility could shut down an entire assembly line and, depending on the event, affect suppliers of other components.

EXHIBIT 1

Automating Transactions Using Intelligent Agents



Key Attributes of Agents

Although researchers disagree as to the exact definition of "agent," there is consensus on its most important attributes. Not all agents, however, must possess all attributes to qualify for "agenthood."

First, agents are **autonomous**, are able to exert control over their own actions, and do not have to be triggered by humans. They are goal-oriented and able to solve problems without input from their owners. For many, the issue of autonomy is contentious. Does an agent merely help its owner make wiser decisions by finding order in information disorder, or by alerting the owner to conditions that must be avoided or exploited? Or does an agent actually undertake actions on the part of the human owner? The answer is both. The level of autonomy allowed depends on the nature of the task at hand and on the comfort-level of the owner. Autonomy doesn't necessarily imply independent action. In some systems, the agent may be fully in charge of controlling the system, pre-authorized to make certain categories of decisions and to initiate actions within an acceptable range. In other systems, the agent may only be allowed to look over the human's shoulder, suggesting alternative actions that must first be reviewed or predicting future outcomes or disturbances so that anticipatory actions can be taken.

Second, agents are **social** and, thus, able to communicate with other agents—and with humans. At the heart of the notion of communication is the sharing of knowledge. Agents by themselves have neither language nor knowledge of particular domains of interest. Nonintelligent search engines can compare sequences of text without domain knowledge or any language ability. The computer, or agent, doesn't understand the information in any deep sense, but it is able to manipulate the information into a form that is understood by the human and other agent, in effect creating communication. For example, consider an agent that is assigned to a shipment moving in early December from New York to Singapore. An inference rule might state that "If a shipment must arrive in Singapore by Dec. 12, then send it via air." The agent associated with the shipment will communicate with transport agents until it finds an agent associated with a flight matching the specific departure and arrival criteria.

Third, agents are **adaptive** and can learn. Like humans, they are able to change their behavior on the basis of observation or experience. For many researchers, an agent is not truly intelligent if it cannot learn. Very simple agents initiate actions based on simple rules that remain fixed. For example, an agent might order 30 personal computers whenever the inventory levels fall below 100 computers. These simple rule-based agents can operate autonomously and can communicate with other agents, but the above task does not embody learning or adapting to new circumstances. Adaptive behavior is associated with the ability to recognize meaningful correlations in data. As the environment changes, the agents recognize the corresponding changes in the correlation structure and change their rules accordingly. For example, Monday might be associated with an increased demand for personal computers because a local manufacturer ships to its distributor on Monday afternoons. A simple rule-based agent might recommend or order a larger number of vehicles every Monday to accommodate the shipments. But what happens if the distributor's schedule changes so that more PCs are needed on Friday? A learning agent would be able to recognize that the correlation between day of the week and shipment volumes had changed and would provide more delivery vehicles on Friday instead of Monday.

Finally, agents can be **mobile**. Mobile agents can migrate across computer networks, representing users in various tasks. Mobility is not a necessary requirement for agenthood. Those who say mobility is not an important attribute believe that most of the tasks performed by agents can be more easily and better solved by stationary agents that exchange messages across the network. Those in favor of mobility as an important agent attribute cite the benefit of reduced bandwidth requirement, especially when large data sets are involved. Mobile agents will likely be most useful in three general areas related to the logistics task. First, mobile agents can assure stability when devices such as laptops or personal digital assistants disconnect unexpectedly from a network. Networks comprised of mobile agents are robust and data is not lost. Second, mobile agents are extremely useful in information retrieval applications where the agent can be sent to a large data source to filter data locally. Finally, mobile agents can effect the dynamic deployment of software or code, for example in an enterprise where local devices require some configurations of code.

Empowering Agents for Action

The earliest commercial agents, introduced in the mid-1990s, focused on filtering information and making buying recommendations (as Amazon.com does through its personalized shopping list). But filtering information and making recommendations is only the first step in the development of agent capabilities. The ability to implement that recommendation or to make a decision based on real-time data provides an additional level of agent functionality.

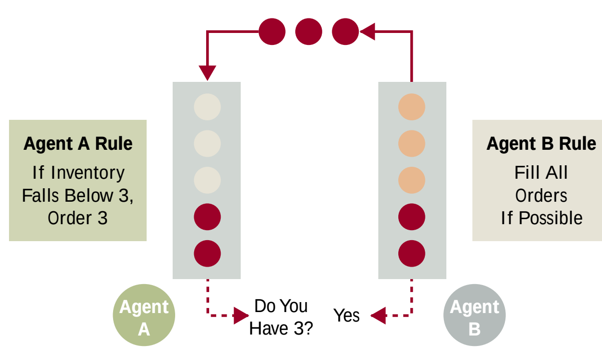
Reconsider the global automotive supplier with scores of facilities scattered across the globe, supplying hundreds of vehicle assembly operations in all parts of the world. The task of the logistics manager is to keep the supply chain operating smoothly by synchronizing the transactions associated with moving parts and materials across the supply chain. In this example, machine agents are capable of observing and accommodating multiple schedule changes in real time—and correlating these changes with the status of current inventories, parts in-transit, and production schedules. When parts shortages or excesses are experienced or anticipated at various locations, agents can alert managers about possible shortfalls. Acting in a support role, agents can even re-prioritize assets and identify alternative supply strategies. Finally, when empowered by their human owners, agents can initiate remedial actions to reposition assets. In short, agents offer significant decision-support capability in the synchronization and alignment of supply and demand.

Tracking inventory levels and part availability in an assembly facility is another task suitable for agent control. To illustrate the functionality of such an agent-enabled system, think about a very simple supply network in which a single distribution center (DC) provides parts to an automotive assembly plant. As shown in Exhibit 2, the assembly facility agent (Agent A) and the supplier agent (Agent B) "negotiate" to assure that parts are released from the supplier's inventory in order to meet a just-in-time assembly schedule. Agent A at the assembly facility observes the fluctuations in inventory level for a particular part as vehicles roll off the assembly line. When inventories fall below safety-stock level, the agent is triggered to place a re-supply order. Agent A queries Agent B, who is monitoring parts inventories at the distribution center, as to whether the order can be filled from its inventory. Agent B checks finished part inventories in the distribution center. If sufficient inventory exists at the DC, Agent B accepts the order. In this system, Agent A operates by the simple rule: "If inventory falls below three parts, then order three parts." Agent B operates by a complementary rule: "Fill all incoming orders, if possible, with existing inventory."

Similarly, a community of agents with more complicated rules and vocabulary can be created for the assembly facility to safeguard against stockouts at the distribution center. If, for example, no inventory is available at the first distribution center, Agent A can be programmed to search its universe of alternative suppliers. The new rule for Agent A might be to search alternative suppliers in an iterative process that pro-

EXHIBIT 2

Rule-Based Agents Manage the Pipeline



ceeds by querying a sequence of the closest suppliers that meet certain cost criteria. Agent A, for example, would query Agent C at an alternative supplier that is 20 miles farther away than Supplier B. If excess parts are in storage at that location within the price range, the agents can negotiate the sale and arrange for delivery to the assembly facility. Suppose Agent C chooses not to release the parts because it expects to receive a higher priority order from a regular customer. In that case, Agent A can continue to search for another agent to query from its catalog of possible suppliers.

Agents that Learn and Adapt

The ability to learn and adapt provides yet another level of functionality to agent capability. The simple agent-enabled inventory control system described in the previous section operates on the basis of simple rules that trigger actions on the part of the agents. Such systems can be fragile in the event of environmental change. Like programmed robots, these systems will continue to perform blindly, if they are not linked to their environment in a sort of "feedback" loop. Learning agents, operating like the human brain, can detect changes in the environment and change behavior accordingly. Much of what happens across a supply chain has both spatial and temporal variations. The task of the agents, like the task of the human brain, is to understand how these temporal and spatial states change over time and to adjust behavior accordingly. To accomplish this, learning agents must be able to perceive events in real time. They must be fast, but internally sophisticated enough to consider the situation completely before giving recommendations. Most importantly, because the world around the enterprise is increasingly dynamic, agents must learn in real time as well. And they must not only learn or turn experience into knowledge; they must also learn quickly.

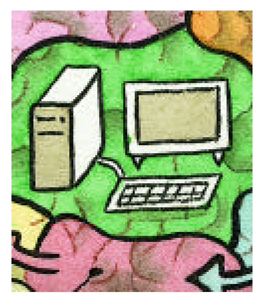
The sort of machine learning described above can be performed by various memory-based approaches to reasoning, of which IBM's Memory Agent is an early, well-known example. Among the newer technologies are associative memory models. In the models, an agent learns to associate a set of observations (or parameters) that describe the state of the system with an outcome. Associative memory agents such as SaffronOne can be based on specific memory and individual behavior.[7] These agents are able to adjust to their observations of the world on a case-by-case basis. Even one case can provide value to the learning process.

Suppose, for instance, a customer enters a store and asks for "X." The sales agent at first doesn't know what "X" means but asks the customer to describe it, and then works with the customer to find it. The sales agent should then simply remember the association of "X" to the customer's descriptions. Whenever that customer, or another, enters the store and again asks for "X," the sales agent can help. Returning to the previous example, if Agent A learns from experience that the supplier always runs short of parts at the end of the month or experiences a shortfall repeatedly as a result of a quality problems, the agent can trigger an increase in the number of parts ordered. Or, if Agent A "learns" that shortfalls are encountered when only three parts are ordered daily, then the agent can increase the order quantity so that shortfalls are avoided. The agent makes correlations between the experienced shortfall, level of demand, and order size. By making these correlations, the agent learns that an order quantity of three is associated with a shortfall and increases its order quantity to five to avoid future shortfalls. This one-trial associative memory approach to learning is a critical competency of associative memory approaches.

Multi-Agent Logistics of the Future

The agents we have described in the previous sections represent the state-of-the-art in intelligent agent software development. Various implementations of all of these agents are alive and functioning within commercial settings. Information agents that filter and sort information continue to support Web-enabled applications. Simple rule-based agents are managing manufacturing operations. And learning agents are assuming roles in logistics management in the LogNet project at The Boeing Company, described in the sidebar on page 25.

Intelligent machine agents support information processing and decision making by reducing the burden of complexity.



As we look further into the "intelligent" future, however, we must confront a radical transformation in how we think about enterprise structure and behavior. We must begin to think about large systems or societies of agents with different roles and behaviors that begin to create and sustain their own communities. These communities of agents are referred to as self-organizing, multi-agent systems. Multi-agent systems consist of hundreds, even thousands, of simple, interacting intelligent agents that pursue a set of common goals or perform some set of related tasks.[8] In these systems, the whole is greater than the sum of its parts. The collaborations and interconnections between many simple agents enable the ensemble to function beyond the capabilities of any single agent in the system.

An analogy is often made between the behavior of multi-agent systems and the collective, swarming intelligence exhibited by ants and bees.[9] These natural variants of multi-agent systems are characterized by flexibility (the colony can adapt to a changing environment), robustness (the colony can still perform when one or more individuals fail), and self-organization (the activities of the colony are neither centrally controlled nor locally supervised). Through self-organization, the colony displays a larger intelligence that is reflected in the coherent and effective behavior of the group. Incredibly, each of the ants follows a few very simple rules of behavior, yet the resulting collective behavior is quite complex and, seemingly, efficient.

Thus, multi-agent systems offer a natural way to think about intelligence. Human intelligence is created through an individual's interaction with other humans and their environment. Group intelligence is more powerful than individual intelligence. Through collaboration, different perspectives and diverse local knowledge can be shared. Multi-agent systems operate in the same way.[10] First, each agent within the system has incomplete information about the total system environment and is restricted in its capabilities. The agents do not have a comprehensive picture of the system, usually only information pertaining to their local environment. And an individual agent cannot directly control the collective system behavior. The control of the system is distributed in the sense we have described earlier.

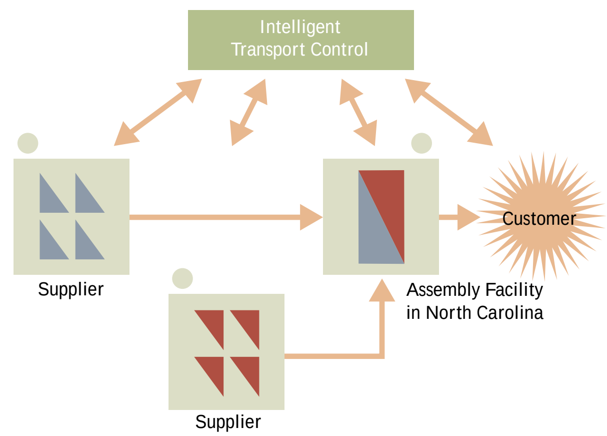
Logistical systems that span the extended enterprise lend themselves naturally to multi-agent technology because they arise within the distributed, or networked, environment of the company. The global automotive supplier network described earlier supports a range of parts manufacturing and vehicle manufacturing sites around the world that have more perfect knowledge about their local operating conditions than headquarters does. Yet each site must cooperate with the others to create a single unified response to customer needs. Moreover, they must do this within the context of multiple, and often contradictory, enterprise objectives such as long-term profitability, near-term stock performance, economic conditions, market trends, and even labor conditions.

Multi-agent systems are especially compatible with distributed and modular enterprise structures. These structures have operations, competencies, databases, and markets that are far flung and locally empowered. They also have functional activities—from human resource management to purchasing and engineering—that are only loosely coupled. Such a virtual and inherently agile organizational structure implies that a supporting agent-network needs to be not only matched to spatially distributed operations; it also needs to be able to coordinate the functional activities across physical and organizational boundaries.

Consider, in Exhibit 3, the case of a shipment that needs to get from a small supplier located just outside Bangkok, Thailand, to an assembly facility in Raleigh, N.C. Currently, human agents book capacity based on predetermined routes, schedules, and rates. However, in the same way that machine agents are now assigned to parts and functions as they move through the supply chain, they also can control the movement of these parts and materials through the transport chain. In the future, it would be possible to build global transportation networks in which packages are able to route themselves, searching for the most efficient route based on local conditions. Packages may even reroute themselves in response to inputs from destination agents based on the reprioritization of needs in various locations. The ability to synchronize the transport of parts and components is illustrated in Exhibit 3. By back calculating transport times and aligning desired arrival times with carrier schedules, customized parts can be scheduled to arrive simultaneously at the point of product assembly. Parts from Asia may be dispatched eight hours earlier than parts from Mexico so that they arrive at the assembly plant loading dock at approximately the same time.

EXHIBIT 3

Synchronous In-Transit Merger



Today, the movement of parts and components is controlled by a variety of logistics functions from the freight forwarder to the various modal transportation providers. Now consider a world in which shipments navigate their way to the customer through a global transportation network defined by a set of intelligent nodes. In this world, each shipment carries with it an identification tag that contains knowledge about its destination, expected time of arrival, and storage and handling requirements. In a very simple "alert" system, this tag—a simple agent—is able to alert the shipper of delays or routing changes. But in a multi-agent system comprised of thousands of agents charged with simple tasks, the transportation network is able to organize itself. In the event of breakdowns or bottlenecks, the package agents can communicate with the node agents to reroute or reschedule themselves to avoid congestion and assure a timely arrival. Agents representing the shipper and the carrier can even negotiate to establish new rates.

Machine agents are not intended to replace human agents but rather to coexist with them—assisting their human owners in tasks for which the agents are better suited. For example, human agents currently handle

Agent-Enabled Decision Support for the Battlefield

The Center for Logistics and Digital Strategy at Kenan-Flagler's Frank Hawkins Kenan Institute of Private Enterprise will use SaffronOne Technology to provide Boeing with intelligent logistics tools for Boeing's Log Net project. Boeing Log Net is an intelligent information system that provides an integrated view of the military logistics environment. The Boeing Log Net system will enable logisticians to gain "situational awareness" of forces around the world, and to make better decisions about how to support them.

SaffronOne, with its innovative associative memory technology, has the ability to handle hundreds of thousands of inputs and make highly accurate predictions in real time. That makes it a perfect match for the enormous volume of complex data that must be filtered and correlated for the coordinated and complex logistics tasks faced by the military.

The U.S. Military is undergoing a transformation in the way that forces are deployed and sustained. As the list of trouble spots grows, the military must be prepared to respond quickly and with a smaller logistics footprint wherever needed. New information technologies, especially new intelligent software, can help military forces become more strategically responsive to crises as they occur.

freight forwarding tasks. But these are exactly the kind of activities that humans should be able to delegate to software agents. Even if all information is available in the open information environment of the Internet, extranets, or intranets, the human ability to manage global communications, routing decisions, or responses to reprioritization of shipments is constrained by an inherent limitation in dealing with large amounts of data with complex correlations. Agents, on the other hand, can near-instantaneously retrieve, filter, correlate, and direct information and decisions across the enterprise.

The challenge of moving parts from "door-to-door" can be likened to a car negotiating its movement across a network of interstate highways and local access roads. Tremendous inefficiencies occur as the vehicle paths are interrupted periodically by traffic lights and toll booths. Agent systems can help remove these inefficiencies by marshaling local intelligence about roadblocks and traffic jams and learning best practices from traffic-smart commuters in response to such impediments.

Start of the Revolution

Clearly, we are at the beginning of an agent revolution. Achieving swarm intelligence within an organizational environment is, right now, a vision for the future. However, as commercial advances by companies like Saffron Technology and the Bios Group suggest, that future is racing toward us very fast. The strategic application of distributed agent technologies and their extension to self-organizing systems promise to be formidable competitive differentiators for the early adopter. The most promising application arenas are those characterized by highly complex logistical systems—systems that are difficult to predict or subject to unpredictable change—and those characterized by highly interrelated events and nonlinear effects. Most global enterprises and value chains—especially those with high product complexity and rapidly changing markets and consumer tastes—qualify.

The current maturity of agent technology is comparable to that of the Internet in the early 1990s. This technology will likely be the basis for agile and intelligent logistics in the not-too-distant future. With early adopters securing first-mover advantage, supply chain managers must ask not whether, but how, to best launch an intelligent agent-based initiative within their organizations and across their extended enterprise.

Footnotes

1 According to Vivek Ranadive, author of *The Power of Now* (McGraw-Hill, 1999), an event-driven company acquires, deploys, and wisely exploits real-time active information in order to instantly sense and respond to the events that drive its business.

2 Otis Port's article in the Aug. 7, 2000 issue of *Business Week* titled "Thinking Machines: Special Report on Smart Manufacturing" surveyed current applications of machine intelligence in manufacturing and production.

3 The application of complexity theory tools to Procter & Gamble's supply chain operations is described in more detail in Rick Whiting's April 12, 2001 article, "Radical Simplicity: Behavior Change for Supply Chains" (www.informationweek.com).

4 Southwest reported that by changing its routing strategy, the company was able to reduce the cargo transfer rate by 70 percent at its six freight hubs, saving millions in wages and overnight storage rental.

5 Recently, enterprise software provider SAP announced the enhancement of mySAP Supply Chain Management to manage adaptive supply chain networks through the use of intelligent agent technology. The enhanced product will enable global visibility through real-time event coordination and management by positioning intelligent software agents at the nodes of the network to provide updates to the SAP software.

6 More details of Turing's probe of computer intelligence can be found in "What Use is a Turing Chatterbox?" by Edmund Ronald and Moshe Sipper which appeared in *Association for Computing Machinery*, Communications of the ACM, New York, Oct. 2000.

7 SaffronOne is a proprietary digital associative memory engine that is able to capture instantaneous associations among very large quantities of data. With incremental learning, the agent learns in real time as information is encountered. SaffronOne represents a quantum leap in speed and memory efficiency over other technologies. For further information, visit www.saffrontechnology.com.

8 The Internet is a prominent example of a multi-agent system. As computers and computer networks are ever more closely linked, they become too complex and difficult to be characterized and managed. Their control becomes more decentralized and all of the components of the Internet begin to act like individual agents.

9 Swarm intelligence is discussed in a May 2001 *Harvard Business Review* article, "Swarm Intelligence: A Whole New Way to think About Business" by Eric Bonabeau and Christopher Meyer.

10 See *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence*, edited by Gerhard Weiss (MIT Press, 1999), and *Multi-Agent Systems* by Jacques Ferber (Addison Wesley, 1999) for a more technical discussion of multi-agent systems.