23 Software Agents Supporting Decision-Makers in Complex Flower Business Networks

Eric van Heck, Rotterdam School of Management, Erasmus University, evanheck@rsm.nl

Wolfgang Ketter, Rotterdam School of Management, Erasmus University, wketter@rsm.nl

"Being Leading in Research for Managing Smart Logistic Networks and Realize Real Innovations"
Prof. dr ir Jo van Nunen – Department Strategy Meeting 2008.

23.1 Introduction

High performing firms are working in business networks with advanced decision making capabilities. Decision making in business networks is a new research area that provides knowledge and insight about how decision rights are allocated and how decision processes are designed and implemented in evolving business networks. In this article we focus on a particular type of support: software agents. Software agents are software programs that act on behalf of users or other programs. Software agents can be autonomous (capable of modifying the way in which they achieve their objectives), intelligent (capable of learning and reasoning), and distributed (capable to being executed on physically distinct computers). Software agents can act in multi-agent systems (e.g. distributed agents that do not have the capabilities to achieve an objective alone and thus must be able to communicate) and as mobile agents (e.g. these relocate their execution onto different processors). Recent research shows that software agents are able to act as a decision support tool or a training tool for negotiations with people. For example, Lin and Kraus (2010) identified several types of agents in several variations of negotiation settings. These agents differ in the number of negotiators, encounters, and attributes they can handle. The identified agents are: Diplomat, AutONA, Cliff-Edge, Colored-Trails, Guessing Heuristic, QOAgent, and Virtual Human. Although software agents are popular in scientific research programs, the use of software agents in real life business situations is limited. We will explore the use of software agents in the flower industry with its complex logistics, commercial, and financial processes on a global scale.

The central research question in this article: what is the potential role and impact of software agents to support decision making in complex business networks? The objective is to explore crucial components for successful support of decision making in complex business networks by software agents.

Section 2 provides the characteristics in human decision making. Section 3 explains where in the complex flower distribution network software agents are able to support decision makers. In section 4 an overview is provided about research challenges of the use and impact of software agents in complex business networks. Section 5 provides conclusions.

23.2 Decision Making

In evolving business networks complex decision making is a core feature for the actors involved. There are three levels of decision making in business networks:

- The first level of decision making is decision that designs the decision making in business network. These decisions deal with the allocation of decision rights, the governance mechanisms that the network uses to coordinate decisions and activities of different actors in the network.

- The second level of decision making is decision that deals with the creation of business network resources. These decisions deal with the investment in the resources of the different business network actors.

  Recent research shows the strengths of biologically inspired network design. Tero et al. (2010) suggest that the slime mould *Physarum polycephalum* forms networks with comparable efficiency, fault tolerance, and cost to those of real-world infrastructure networks—in this case, the Tokyo rail system. They built a template with 36 oat flakes (a favored food source) placed to represent the locations of cities in the region around Tokyo. They put P. *polycephalum* on Tokyo itself and watched it go. They found that many of the links the slime mould made bore a striking resemblance to Tokyo's existing rail network. The research results suggest that good and complex solutions can emerge from simple rules, and that this principle might be applied elsewhere. The next thing is to discover and use these rules to enable other networks to self-organise in an "intelligent" fashion without human intervention – for example, to link up a swarm of robots exploring a dangerous environment, so that they can talk to each other and relay information back to base (Economist, 2010).

  The core mechanisms needed for adaptive network formation can be captured in a biologically inspired mathematical model that may be useful to guide network construction in other domains.

- The third level decision making are decision that deal with utilization of business network resources. These decisions deal with the level of utilization of resources by the different business network actors.

23.3 Complex Flower Business Network

We illustrate the third level with key decisions by each of the actors in the complex flower business network. This network is linking thousands of flower growers via the Dutch flower auctions (FloraHolland) to the flower transporters, wholesalers, retailers, and consumers. The Netherlands is the world's leading producer and distributor of cut flowers and potted plants. This industry consists of about 10,000 growers and nearly 5,500 buyers. Growers typically are family businesses, while buyers represent both large and small wholesalers and retailers. The Dutch dominate the world export markets, with around 59% world market share for cut flowers and 48% world market share for potted plants. The Dutch flower auctions established and owned by grower cooperatives play a vital role in Holland's leadership of this industry by providing efficient centers for price discovery, and the exchange of flowers between buyers and sellers. This sector accounts for 6 percent of total export value and 2% percent of the Dutch labor market. The world's two largest flower auctions are in Aalsmeer and Naaldwijk both located in the Netherlands and operated by FloraHolland. Every day the six Dutch auction centers traded over approx. 44 million flowers and 4.8 million potted plants resulting in 125,000 transactions daily, generating together over 4.1 billion Euro in annual sales of cut flower and potted products from the Netherlands and other producers such as Ethiopia, Israel, Kenya, and Zimbabwe. The main export countries are Germany, United Kingdom and France. Within Europe, the main mode of transportation is by truck. Products meant for export to countries outside Europe is brought to Schiphol Airport and flown to destinations all over the world, where they can be sold within one day.

This research is an important step in harnessing the complexity of combinatorial human decision-making in complex, information-rich and dynamic environments such as the Dutch flower auction and distribution network. Improving the quality of decisions will make the Dutch flower industry more competitive in the world market. The Dutch flower network presents additional challenges of this nature which we plan to address in the future. In Figure 1 we show additional places in the network where learning software agents can empower humans in their decision-making capacities, have a positive impact on economic activity, and strengthen the Dutch position on a global scale.

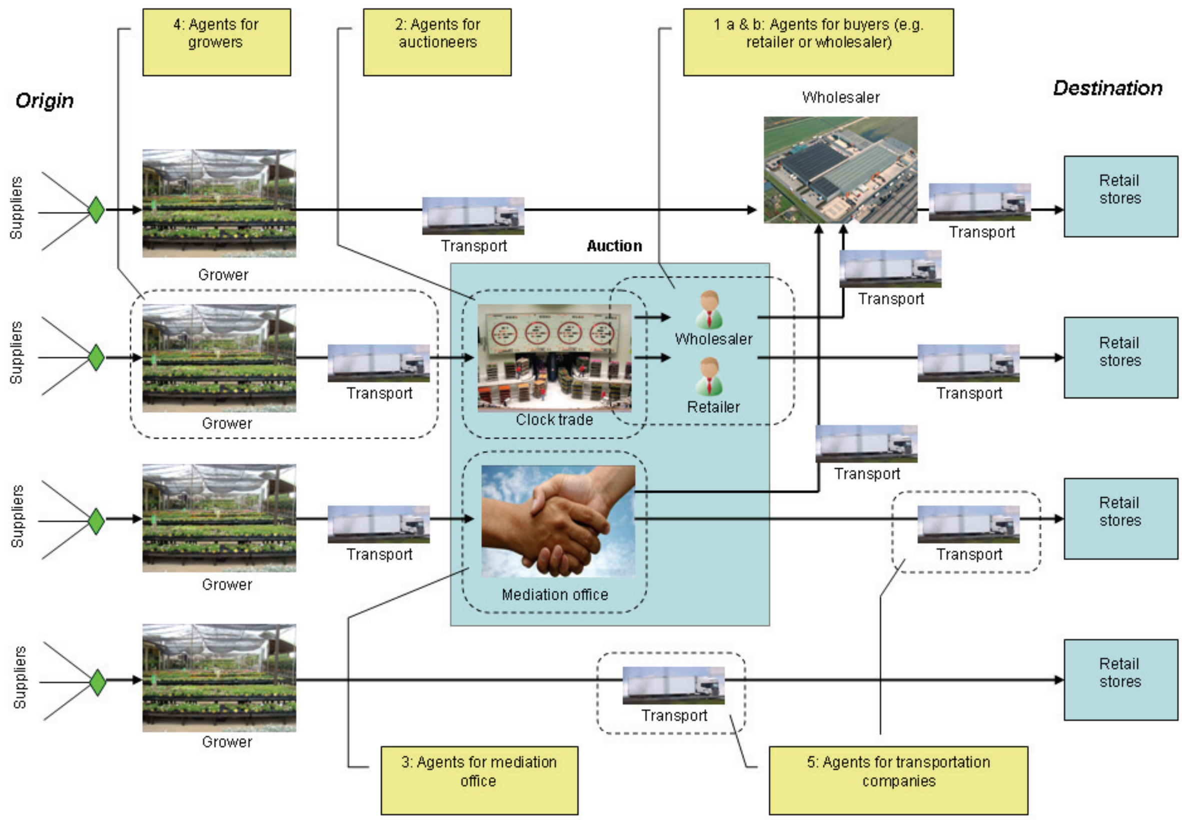

Figure 1: Applying Learning Software Agents in the Complex Flower Network.

We have a long-term relationship with FloraHolland that has not only produced very good research, such as Kambil and van Heck (1998), Koppius (2002), Kambil and van Heck (2002) and Koppius et al. (2004). It also led to practical insights about the design and implementation of online auctioning and distribution aspects in the Dutch flower industry. For example, FloraHolland used the outcomes of research of Kambil and van Heck (1998; 2002) such as how to design and implement online auctioning using the developed stakeholder/process framework. The research on screen auctioning (Koppius et al., 2004) resulted in a better understanding of the impact of digital product representation and decoupling from distribution. The results of researching Buying-at-a-Distance auction (Koppius, 2002) resulted in a better understanding of online auctioning and its impact on price levels and buying behavior.

Online auctioning was last year growing with 35% in terms of transactions and became an important digital channel for FloraHolland, wholesalers, and retailers. For the coming years the design and implementation of learning agents in online markets and the decoupling from auctioning and logistics and distribution with new forms of distribution will be create new opportunities to create value for stakeholders involved (see Table 1).

The distribution network consists of three sub-networks. The first sub-network deals with the logistical flow of perishable flowers from growers to the final consumers. The second sub-network deals with the financial flow from the final customers to the growers. The third sub-network is information that is flowing among the different actors in the business network. Adaptive network formation is making constantly tradeoffs among the cost, efficiency, and resilience of the expanding network. The network expands towards areas with customers that are able to buy flowers taking into account distributions and communication costs.

Table 1: Decision Making Characteristics of Flower Business Network Actors.

Business Network Actor	Decision Process	Crucial Information	Software Agent Support
Flower grower	Decision to sell its flowers.	Supply information (own, other growers); Demand information (historical, current); Specific	Comparison of different sales channels (auction, brokerage, direct); Timing support (for example day of the week)
Auctioneer	Decision to auction off flower lots.	Supply information (historical, current day); Demand information (historical; current day); Minimum units to auction; Auction speed;	Support of the starting price for each auctioned lot; Support to determine the auction speed; Support to determine the minimum transaction amount.
Wholesaler	Decision to buy flowers; Decision to bundle and transport to retailers.	Supply information (historical, current day); Demand information (historical; current day); Specific order information;	Support purchase decision (price level, quantity) Support based on preference modeling; Comparison of different procurement channels (auction, brokerage, direct);
Transporter	Decision to bundle orders and provide shortest routes.	Specific transportation details (traffic routes, traffic jams etc)	Support for bundling transports; Support for route optimization;
Retailer	Decision to buy flowers.	Supply driven versus demand driven approach	Support purchase decision (price level, quantity) Comparison of supply versus demand driven supply chain strategy
Consumer	Decision to buy flowers.	Price, quality and delivery time and delivery reliability of retailer.	Comparison different offline and online retail stores Support based on consumer preferences.

Advanced decision support systems and software agents promise to assist businesses by acting rationally on behalf of humans in numerous application domains. Examples include procurement (Sandholm et al., 2005), scheduling and resource management (Collins et al., 2002), Internet shopbot agents (Haeubl and Trifts, 2002; Montgomery et al., 2004), and personal information management (Myers et al, 2007). We research rapid-fire Dutch flower auctions and distribution systems whereas research so far has dealt only with slow ones taking several days (Carare and Rothkopf, 2005). In this research we plan to enable people to interact with an agent in a collaborative manner. The agents could predict the appropriate next steps, helping to speed up, and improve the quality of a user's overall decision process. Such agents are sometimes referred to as expert or interface agents (Maes, 1994; Rich and Sidner, 1998). There has been significant academic research on personalization and recommendation systems (Amomavicius and Tuzhilin, 2005) to model user preferences. The most prominent approach is based on collaborative filtering (Goldberg et al, 1992).

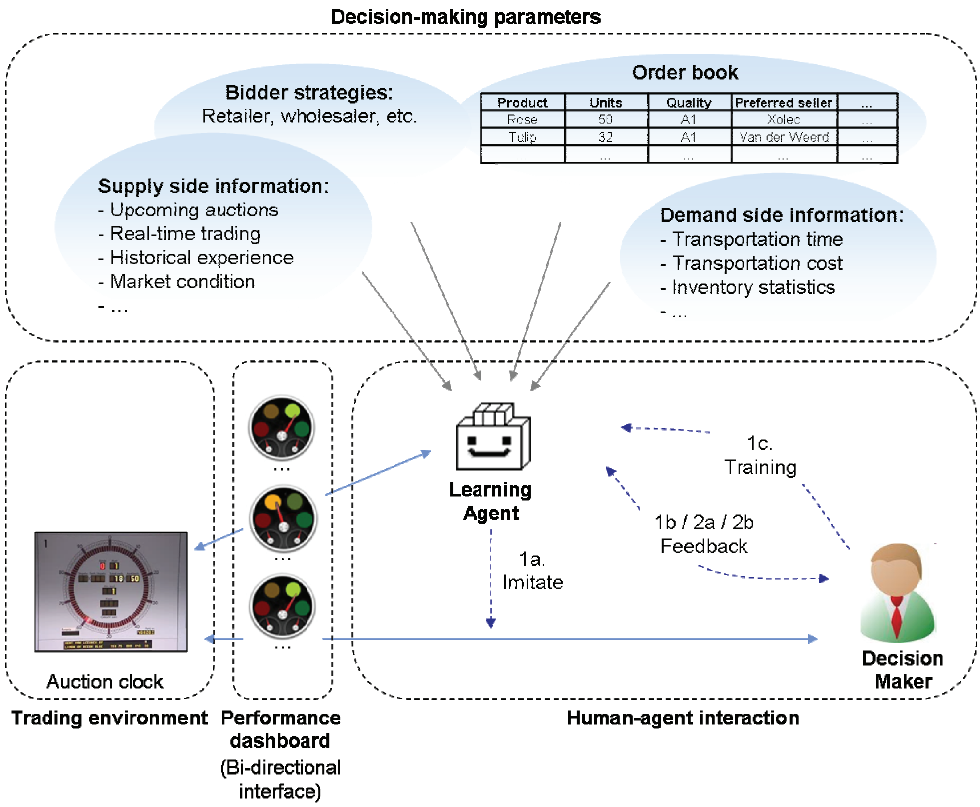

Figure 2: Human Decision Making Supported by Learning Software Agents.

The proposed research will draw on the fields of computer science, economics, information systems, machine learning, operation research, and supply chain management to develop techniques to analyze human behavior and to evaluate intelligent decision support systems. Our research will proceed by incremental construction and evaluation of a prototype learning agent. First, we will build a model of human preferences based on machine learning research. Second, we will draw on research in recommender systems and operations research to incorporate the model into an agent that will acquire and display information and recommend actions that are in the best interest of users given the learned preferences. We expect to extend the current literature in these areas, since we are creating human preference models which are based on explicit and implicit human-agent interaction. Figure 2 shows the preference elicitation methods (dashed lines) and the recommendation models (Feedback).

Below we list, as shown in Figure 2, the novel characteristics we expect to demonstrate in our learning agent:

1. The agent will learn implicit and explicit human preferences over time through:
    a. Observing user behavior through tracking of the interface – we will begin with simulations and historical data and then move toward real-world deployment.
    b. Adapting based on user feedback.
    c. User survey and teaching through examples.
2. The agent will recommend actions based on:
    a. A formal model of human preferences and the business domain.
    b. Order-book as well as other contextual constraints.

We will evaluate our approach through laboratory and field experiments with human subjects, using multi-agent simulation and real world data from the Dutch flower auctions, wholesalers, and transporters.

23.4 Challenges

The proposed research will draw on the fields of computer science, economics, information systems, machine learning, operation research, supply chain management, and software engineering to develop techniques to analyze human behavior and to evaluate intelligent decision support systems (Collins et al. 2009, 2010a). The research may also lead to insights in facilitating human decision making in other complex environments. Concretely, we will contribute to human preference elicitation and representation, to decision recommendations based on human preferences, to human-agent interaction, and to agent architecture.

What is particularly exciting about researching preferences in the context of the DFA is that not only has FloraHolland granted researchers data, but moreover, those data are not anonymous. This means that researchers can not only build models of user preferences, but further, they can test the accuracy of their models by through testing and interviewing users. This research is getting underway in the Netherlands, and involves a team of interdisciplinary researchers that includes both computer scientists and psychologists. This is a great opportunity to facilitate the business science interaction and to speed up the transfer of knowledge into business.

Roughly ten years ago, FloraHolland introduced the remote buying application (RBA), a computer interface that enables buyers to bid in the DFA without being physically present in one of the auction houses. As the name suggests, RBA facilitates remote bidding. RBA opens up a world of opportunities for bidders. A small retailer in the south of France need no longer send a representative to the Netherlands once or twice per week to procure flowers for him, but rather his representative can bid daily in the comfort of his own home. But that is all that the RBA does. It does not make bid recommendations or manage information in a way that lowers the burden of cognitive processing for the bidder.

We are proposing to engineer intelligent agents for the complex business network of the DFA that provide decision support to auctioneers and bidders (Collins et al. 2008, 2010b). To do so, we must overcome technical challenges in preference modeling and elicitation, prediction (Ketter et al. 2009), and optimization. User interface design is a further challenge, but one which is at least partially solved (on the buyer side) by the existing RBA, upon which we plan to build our initial prototypes.

This research is very challenging since it demands a unique end-to-end modeling, i.e. going from empirical models based on real-world data to agent-based simulation, to agent-human lab experiments, and finally real field experiments. This really challenges researchers to obtain this unique skill set and to work in interdisciplinary teams.

23.5 Conclusions

The goal of our work is to develop and evaluate highly personalized adaptive learning agents to complement the cognitive and computational capacity of humans, while leveraging the experience and contextual knowledge of seasoned DFA decision makers (auctioneers and buyers) to facilitate decision making processes. These agents will collaborate with their users to gather and present information and recommend action. To work effectively and efficiently in a supply chain environment, these agents will learn the interests, habits, and preferences of their users with respect to the decision context.

Research needs an application and the Dutch flower auction network is a complex, challenging, and economically important application domain. This makes it an ideal environment for our learning agent research. The knowledge that will be gained during this research can then be applied to many other supply chain decision-making settings, such as the resource allocation problem of container ships in the Rotterdam harbor.

Acknowledgements

This paper was written in memory of Prof. Dr. Jo van Nunen. Jo had a great personality, was a convinced scientist, a leading figure in logistics, and a passionate believer in his ideals. Jo is greatly missed, especially with his encouragement for young researchers to bring out the best in them through his motivating and joyful manner, and to stimulate many positive developments inside and outside of the department.

References

Adomavicius, G. and A. Tuzhilin, Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. *IEEE Transactions on Knowledge and Data Engineering*, 2005. 17(6): p. 734-749.

Carare, O. and M.H. Rothkopf, Slow Dutch Auctions. *Management Science*, 2005. 51(3): p. 365-373.

Collins, J., W. Ketter, and M. Gini, A Multi-Agent Negotiation Testbed for Contracting Tasks with Temporal and Precedence Constraints. *International Journal of Electronic Commerce,* 2002. 7(1): p. 35-57.

Collins, J., Ketter, W., and Gini, M. 2008. Flexible decision support in a dynamic business network. In:Vervest, P., van Liere, D., and Zheng, L., editors, The Network Experience – New Value from Smart Business Networks, pages 233–246. Springer Verlag.

Collins, J., W. Ketter, and M. Gini. 2010a Flexible decision support in dynamic interorganizational networks. *European Journal of Information Systems*, 19(4), September.

Collins, J., Ketter, W., and Gini, M. 2009. Flexible decision control in an autonomous trading agent. Electronic Commerce Research and Applications, 8(2) 91–105.

Collins, J., W. Ketter, and N. Sadeh. 2010b. Pushing the limits of rational agents: the trading agent competition for supply chain management. *AI Magazine*, 31(2):63-80.

Economist, The (2010), A Life of Slime: Railways and Slime Moulds, 23 January 2010, p. 71.

Goldberg, D., et al., Using collaborative filtering to weave an information tapestry, in *Communications of the ACM*. 1992, ACM. p. 61-70.

Haeubl, G. and V. Trifts, Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids. *Marketing Science*, 2000. 19(1): p. 4-21.

Kambil, A. and E. Van Heck, Reengineering the Dutch Flower Auctions: A Framework for Analyzing Exchange Organizations. *Information Systems Research*, 1998. 9(1): p. 1-19.

Kambil, A. and E. van Heck, Making Markets: How firms can design and profit from online auctions and exchanges, Harvard Business School Press, June 2002.

Ketter, Wolfgang, John Collins, Maria Gini, Alok Gupta, and Paul Schrater (2009), Detecting and Forecasting Economic Regimes in Multi-Agent Automated Exchanges. *Decision Support Systems*, 47, 4, p. 307–318, 2009.

Koppius, O.R., Information Architecture and Electronic Market Performance. 2002: Erasmus Research Institute of Management (ERIM, PhD Dissertation), Erasmus University Rotterdam.

Koppius, O., E. van Heck, M. Wolters, The importance of product representation online: Empirical results and implications for electronic markets, *Decision Support Systems* (2004) 38, 161 – 169.

Lin, R. and S. Kraus (2010), Can automated agents proficiently negotiate with humans?, Communications of the ACM, 53, 1, p. 78-88, Maes, P., Agents that reduce work and information overload. *Communications of the ACM*, 1994. 37(7): p. 30-40.

Myers, K., et al., An Intelligent Personal Assistant for Task and Time Management, in AI Magazine. 2007, Association for the Advancement of Artificial Intelligence (AAAI). p. 47.

Rich, C. and C.L. Sidner, COLLAGEN: A Collaboration Manager for Software Interface Agents. User Modeling and User-Adapted Interaction, 1998. 8(3): p. 315-350.

Sandholm, T., et al., CABOB: A Fast Optimal Algorithm for Winner Determination in Combinatorial Auctions. *Management Science*, 2005. 51(3): p. 374-390.

Tero, Atsushi, Seiji Takagi, Tetsu Saigusa, Kentaro Ito, Dan P. Bebber, Mark D. Fricker, Kenji Yumiki, Ryo Kobayashi, Toshiyuki Nakagaki (2010), Rules for Biologically Inspired Adaptive Network Design, *Science*, 22 January 2010, Vol. 327. no. 5964, pp. 439 – 442.

Van Heck, E. and P. Vervest (2007), Smart business networks: how the network wins, *Communications of the ACM*, 50, 6, p. 29-37.

Van Laarhoven, Peter et al. (2008), Logistiek en supply chains: innovatieprogramma, December 2008.