SOCIAL SIMULATION WITHIN CONSUMER GOODS INDUSTRY: THE WAY FORWARD

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ABSTRACT

Simulation based research, especially for social systems have grown in size and matured in the last two decades. But in spite of high potential impact, adoption and applicability within businesses is relatively low, especially so in the consumer goods industry. This paper indicates some key focus areas in research which, if pursued consistently, are most likely to have the highest impact. These areas are: providing complementary predictive capability to standard market mix models, modelling disruptive changes in the market, increased partnership with the automated personalized algorithms research community and focussing on toolkits which can be directly used by businesses for training and research purposes. It goes on to point out strategies which can be adopted by the research community which will increase the chances of effectively focussing research onto the areas mentioned above.

INTRODUCTION

Simulations have been widely used across multiple functions within industries over the years – be it in product design, process optimization or in general business simulations used for training purposes (Summers, 2004; Faria et al., 2008). However, it is only recently that simulations have entered the arena of organizational, market and consumer research, mostly as a complement to more traditional statistical and econometric techniques (Garcia, 2005; Delre et al., 2007; North and Macal, 2007). This can only be attributed to the growing awareness of the fact that markets, consumer groups, supply chains, and even whole organizations can be treated as complex systems, as they have unique characteristics which lend themselves to bottom-up analysis (Bonabeau, 2002; Robertson, 2004; Jager, 2007).

However, in spite of its growing popularity, the use of simulation based approaches such as Agent Based Modelling and Simulation (ABMS), have made only rudimentary in-roads into traditional business oriented applications such as marketing, supply chain optimization, optimization of organizational complexity etc. This paper discusses some of the recent developments in simulation based research relevant to applications within industry – focussing primarily on research within social and behavioral sciences, rather than on the use of simulations from the technology and organizational focus. This paper argues that the state of ABMS research and applications is at an important juncture and would require a sustained and focussed effort from both researchers and practitioners in order to reach similar levels of success as traditional quantitative methodologies of analysis. This paper takes the lead on presenting some of the key issues that researchers in both academia and industry need to focus on, if the science of complex adaptive systems and social simulations has to be established as a standard within businesses.

It is well known within the research community that ABMS and other bottom-up simulation based methods have a number of advantages over traditional methods in analyzing large networked systems which exhibit typical characteristics of complex adaptive systems – *emergence, heterogeneity, connectedness and evolution* (Bonabeau, 2002). Consumers are generally heterogenous in tastes and preferences and competition leads businesses/firms intervene through pricing and promotions, packaging, advertising campaigns etc. very regularly. Additionally, markets may be subject to exogenous shocks such as new product launches, evolving nature of consumer preferences and even lateral non-linear interactions through word of mouth and social networks. All of the above, acting on individual constituents or subsets of constituents give rise to various interesting macro level phenomena, such as high volatility, crashes or even exponential growth (Adebanjo and Mann, 2000; Ailawadi et al., 2001).

It needs to be noted that businesses differ from each other a great deal, not just across industries but even within a particular industry. Companies generally embody their own product portfolio, market focus, internal management structure, R&D philosophy and ways of working etc. Hence, the motivation behind adoption of new techniques both in research and applications will be different from business to business – and a meta study such as this may not be applicable in all respects to every business under its purview. However, the aim is to

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pick up general trends and identify overarching patterns governing the use of simulation based modelling within specific industries. This paper focusses on the fast moving consumer goods (FMCG) industry in particular but also touches upon issues related to consumer goods in general. Social simulation and complexity is relevant for most other industrial sectors, but a more general analysis is beyond the scope of this paper.

This paper is organized as follows. The next section provides a brief review of the state of the literature which is relevant to industrial applications of social simulation research. Next, we present the main focus areas for research, which in the opinion of this author, will have the biggest impact on encouraging businesses to adopt social simulation techniques on a more regular basis. Following that, we present some broad strategic directions within the research community, which are likely to maximize the chances of success in the focus areas mentioned in the previous section. We conclude in the following section.

BACKGROUND

We start by reviewing a sample of the simulation based literature dealing with topics relevant to industry with particular emphasis to consumer goods markets. A substantial number of high quality papers have been published in the literature relevant but lack of space prevents us from providing an exhaustive review. Hence, we shall touch upon a few ones which seem to have the most relevance.

One of the core areas where simulations and simulation based research is likely to have direct impact is around optimization of marketing spends. Consumer goods businesses in partnership with retailers and supermarkets are usually involved in heavy marketing interventions – pricing, promotions, product placement, advertisement to name a few – all of which involve large marketing budgets (Blattenberg and Wisniewski, 1989; Ailawadi et al., 2001). Additionally, with the advent of social media and online networks, radical new possibilities have opened up in reaching out to their consumers.

As mentioned by (Gilbert et al., 2007) and (Jager, 2007), consumer goods markets exhibit complex behaviour at multiple levels. The role of traditional modelling paradigms is highly restricted in many cases where markets undergo exogenous disturbances, either through disruptive innovations or through exogenous shocks (Bonabeau, 2002). Even during normal steady states, forecasting and analysis is only possible of aggregate phenomena, for instance market specific demand forecasting, price elasticity estimation etc. But actual examination of micro-level dynamic properties such as product take up, diffusion of information and shocks are difficult to undertake using these traditional techniques. As will be shown subsequently, this is where agent based modelling shows a lot of promise, given the focus on agent level phenomena and interactions (Adebanjo and Mann, 2000; Garcia, 2005; Delre et al., 2007).

Whereas traditional marketing models, based on general linear models, logistic regression etc. are able to provide a lot of good insights on the overall structure and macro level dynamics of markets, micro level characteristics such as product switching, lock-ins, loyalty and other psychologically motivated behavioral traits can only be studied through more disaggregated techniques such as ABMS and micro-simulations etc. (Janssen and Jager, 1999, 2003; Adjali et al., 2005). ABMS in particular can model social influences, peer pressure, dynamic feedbacks etc., which traditional top down modeling paradigms fail to capture robustly (Tesfatsion, 2006). Additionally, ABMS is not restricted to strong assumptions regarding distributions and error terms in any model and hence provides the flexibility of addressing the "natural" description system in a more complete manner (Bonabeau, 2002).

Any modelling paradigm for social systems has to be reliable and robust in order to address real world phenomena. In fact, the modelling paradigm should itself inculcate and internalize the principles of validating those models. This assumes far greater importance in the context of real world applications within any sphere. A large amount of literature within the agent based modelling community has addressed this issue at many levels. A number of authors, (Fagiolo et al., 2005; Windrum et al., 2007; Garcia et al., 2007; Midgley et al., 2007) stress the fact that validation in agent based models should be key, and should possess a "satisfactory range of accuracy" matching the simulated model to the real world. They also point out that the validation methodologies should address model accuracy at multiple levels – macro and micro and possibly at intermediate levels as well. The importance of verification and validation can never be overstated in the context of using ABMS in industry. This is a topic we shall revisit in the subsequent sections.

Although ABMS has been popularized over the last two decades, it is only recently that consumer goods industry specific research and case studies have made an appearance in the literature. The important aspect of acceptability has been addressed by (Midgley et al., 2007), (Marks, 2007) and more recently by (Rand and Rust, 2011). Midgley and Marks provide a framework within which rigorous testing of models created using agent based technologies is possible. They stress the modelling of "complete systems" instead of parts, and to do it, take into account the heterogeneity that exists within *different players* of the same system (for instance, different firms, different supermarkets and of course, different consumers). Rand and Rust addresses similar issues on the acceptability of agent based modelling in marketing research, and provide directions towards further rigor in the analysis via the example of product diffusion through an agent based version of the well known Bass Model (Bass, 1969).

Heterogeneity within a system can reduce predictive power within traditional top-down methods as has been shown in (Sengupta and Glavin, 2010). The authors build a simulation of a consumer goods market within a multi-agent framework, set out a rigorous validation methodology at multiple levels using individual purchase data and show that a simple single parameter multi-agent model can achieve significantly higher *shopper level* as well as *market level* predictive accuracy on out of sample data, compared to a market share based probabilistic choice model. In a recent paper (Sengupta and Glavin, 2012), the authors extend the above rational choice based consumer model by incorporating psychological drivers explicitly into the behavior of agents. This extension is shown to improve prediction accuracy further at both micro and macro levels as compared to the earlier work. In an illuminating article on the use of simulations within an industrial context, (North et al., 2010) examines how ABMS technology has been used within consumer goods companies for building market simulations for actual decision making. The retail sector, through which the majority of consumer goods industry supply their products to consumers, has also seen a rise in the use of ABMS for analysis and decision making (Siebers and Aickelin, 2011; Siebers et al., 2011).

FOCUS AREAS FOR ABMS

ABMS holds a lot of promise in the fields of marketing and consumer science. However, in spite of its exponential growth within the research community, it is yet to have a significant presence in marketing and the consumer goods industry. Over the last two decades, the number of start-ups and consulting agencies who employ ABMS technology have been rising dramatically, but how much of the available expertise is actually used to embed ABMS systems within businesses is questionable as well. There are definitely some documented cases where ABMS is being used, most notably in the areas of supply chain optimization, distribution networks etc. (Siebel and Kellam, 2003; North and Macal, 2007; North et al., 2010). But the use of *social* simulation is still in its infancy. In this author's own experience, convincing senior stakeholders in businesses, of the immediate impact of ABMS in their daily operations when standard analytical techniques have been considered as best practise for many years, is an uphill task.

However, with growing awareness about the usefulness of computational modelling techniques, with increasing availability of advanced computational resources, and with a large body of high quality research to draw from, it is the author's contention that the ABMS technology is uniquely positioned to deliver high impact solutions to a myriad of issues which the consumer goods industry is facing. We discuss a few challenging areas where ABMS research can and should focus on in the near future and which carries a high probability of capturing attention from stakeholders within businesses.

Complementary Predictive Capability

One of most widely used quantitative techniques for market analysis within the consumer goods sector is Market Mix Modelling (MMM). This uses various types of multivariate regression techniques to identify effects of primary marketing variables (such as price, promotions, distributions and media spend) on market shares and sales of products. MMM typically uses aggregated sales data to build these models, and in general, have found wide acceptability as a marketing tool in many companies.

Standard MMM models are usually highly sophisticated and uses advanced econometric techniques. However, partly because of the analytical rigor involved and partly because of the top-down nature of these models, they are not suitable for making targeted predictions at levels below the one at which the models have been constructed. ABMS seems to be just the right technology to fulfill this gap and provide a more complete picture of the market. One way is to use ABMS as standard predictive technology $a\ l\acute{a}$ (Sengupta and Glavin, 2010) and (Sengupta and Glavin, 2012). However, a more fruitful way of using this technology is to *explore the space* of possible models at the micro level, which give rise to the appropriate MMM model at the macro level. Appropriate micro level data is certainly available nowadays, in the form of point of sale records and loyalty card based transactions data from retailers and shopping panel data collected by various agencies.

Modelling Disruptive Changes

Consumer goods markets are usually in a state of flux, with a constant stream of new products being launched, old ones being re-packaged and/or re-branded or being taken off the market completely. Standard quantitative techniques being used today to model markets require two to three years of data for identifying seasonal patterns and effects of market interventions. This is normally not an issue with established products and categories, but products launched in the near past cannot be modeled this way. This can and does create problems for practitioners when deciding on the optimum marketing mix, both at the time of the launch and for a significant time afterwards as witnessed in the unreasonably low rate of new product take up in the consumer goods sector (Schneider and Hall, 2011).

ABMS once again, can prove to be useful if practical toolkits can be built which helps a practitioner to handle this issue. These potential toolkits have to embody a number of different aspects of a product launch – for instance, appropriate market mix supporting the launch, characteristics of the target market, competition and its response, dynamics of information diffusion, market reactions to new launches and corresponding feedback effects as well as non-linear interactions. Depending on the category and nature of the new launch involved, a number of other idiosyncratic issues may have to be addressed within the same toolkit. The challenge is not only to be able to build repeatable models incorporating all of the above, but to be able to verify and validate them to a high degree of accuracy using retrospective data. One may refer to (Marks, 2007) in order gauge the level of challenge facing the modeler in such situations – especially with respect to the issue of *sufficiency versus necessity* in model validation. According to (Marks, 2007), one of the reasons why ABMS has not been fully accepted by the economics profession, is because "simulation can, in general, only demonstrate sufficiency, not necessity" and that "simulation can disprove a proposition...but cannot prove it...", unless the degrees of freedom in the model are low and hence, it is possible to exhaustively explore all possibilities.

Solution Space for Automated Algorithms

With the advent of online shopping and retail, the use of automated (often personalized or customized) algorithms have become very popular (Dias et al., 2008). Such algorithms cluster consumers based on past history and demographics, make product recommendations to the consumers based on similar information and often link consumers based on shopping profile in order to improve take up of recommendations.

These algorithms have so far been purely within the domain of online retailers selling durable consumer goods such as books, DVD/CDs of movies and music albums, consumer electronics etc. However, online grocery and FMCG is becoming increasingly popular and major retailers are pushing to have an online presence, followed closely by the manufacturers themselves. With fast changing shopping habits, the use of automated algorithms will become more widespread as an important driver of shopper behaviour. Moreover, such algorithms are becoming more and more ubiquitous given the increased access of potential consumers to the internet, using a large variety of mobile devices.

While the applied mathematics and data mining research community has been at the forefront of popularizing these algorithms, the ABMS research community seems to have largely ignored this area. This is puzzling at first glance as there seems to be some significant overlap within both the areas – at least as far as addressing individual choice and behaviour is concerned. The main reason behind this divide is probably methodological as well as philosophical. Yet both areas would benefit from using an inter-disciplinary approach in a number of ways – improving prediction accuracy and hence adding to validation methods, providing the ability to test algorithms speedily and realistically without resorting to expensive live tests, as well as providing insights on behaviour where there were previously none. At the very least, algorithms embedded in mobile systems would provide a rich source of social network data, which currently is difficult to obtain. Additionally, it would allow the ABMS community direct access to the online shopping business – a small market currently, but one which is growing at a fast rate.

Market Simulation Toolkits and Validation

This is an area where a number of researchers and practitioners have already been active, as evidenced in the number of market simulators available off the shelf. For instance, AnyLogic (`http://www.xjtek.com/`), MarkStrat (`www.stratxsimulations.com/`), ThinkVine (`http://thinkvine.com`) to name a few. Some of these in fact incorporate ABMS as part of the modelling toolkit under the hood. However, these are often general pieces of software which need to tailored for specific markets using data provided by clients – hence may miss out on capturing some key market specific artifacts within the simulation engine. Additionally, one of the biggest drawbacks of using off the shelf solutions is that they tend to be implemented as "black boxes". As a result, the verification and validation methodology is hidden from the final user and which also points toward the reason why these simulation platforms are not part of standard practise as yet.

However the contribution of the ABMS research community should not just be in building the underlying simulation engine involving consumers, products and retailers. This should be tied with modelling disruptive changes in the market place as well, and should enable the user to examine non-standard market phenomena.

More quantitative research is necessary in the area of verification and validation of ABMS based models. This is challenging problem to overcome, as validation of ABMS models is inherently difficult – usually due to the nature of the data, presence of non-linear interactions and hidden complexities within the system under study. However, this is definitely one area where the social simulation research community needs to invest more resources into, given the potential benefits in the future. Important lessons on the needs and requirements of any business, when implementing advanced decision tools, can be found in the excellent article (Divakar et al., 2005).

THE WAY FORWARD

In the preceding paragraphs, we discussed the status of social simulation research with particular emphasis on consumer goods industry. We briefly covered the state of the literature on this topic which directly impacts the needs of this industry and then examined a few key areas where more focus ought to be given by the research community in order to embed this technology more solidly with businesses. Currently, interest within industry is definitely present, but is at a nascent and experimental stage. Yet the promise of this technology and what it can achieve in terms of impact is easily visible to *researchers* active in this field. This author proposes that the best set of strategies at this point in time, for the ABMS community, are those which focus more on achieving the same for the *potential practitioners* within the industrial sector. The list of potential practitioners include experts in consumer analytics, brand and marketing managers and executives.

An important step in this direction will be taken if the fields of economics/econometrics, behavioral economics and marketing are willing to accept social simulation more readily than is done currently. This has not been easy traditionally, as is pointed out in (Marks, 2007), but important steps have been taken already in many areas of social systems modelling and economics. However, marketing as it is practised within industry, is still dominated by top-down quantitative techniques such as time series analysis, different flavours of multi-variate regression including Bayesian methods, discrete choice modelling, Markov Chain Monte Carlo (MCMC) etc. See (Frances and Montgomery, 2002) for more details. While these techniques are no doubt rigorous and proven to work well within their own domains, they lack the flexibility, reach and usability provided by the bottom up methodologies. The attempt from the ABMS research community should be to provide an important compliment to such techniques – with solid evidence of how ABMS can extend and improve the reach and usability from the point of view of managers and practitioners.

The key point at this stage is to encourage more and more empirical work in the field of ABMS led social science research, focussing on the verification and validation aspects of model building. There is strong evidence to show that such empirical research is possible and potentially useful to businesses and practitioners (Marks, 2007; Midgley et al., 2007; Sengupta and Glavin, 2010; Rand and Rust, 2011; Sengupta and Glavin, 2012). Constraint in space prevents a more detailed exploration of the models and modelling paradigms in these papers, but it is sufficient to say that a strong verification and validation methodology coupled with relevant business application centric approach, makes them useful examples to follow in the future. If the aim is to embed this technology within industry as a standard complement to existing toolkits, the evidence has to be forthcoming on the usefulness of this technique to add value over and above that provided by the existing ones. The nature of this evidence and the areas where they may be best explored has been specified above. However, to carry out this exercise on a suitably large scale, a few primary requirements have to be satisfied: availability of data of sufficient level of granularity and enough information (in order to identify not just agent level characteristics but also the complex inter-relationships), comparable models built on the same or similar data using standard techniques (to be used as benchmark to determine the value addition made by ABMS) and suitable questions and problems forthcoming from the practitioners in the field and not just what a researcher might think is relevant for practitioners.

Organizations often partner with specialized external firms in order to carry out their quantitative market research on the vast amounts of data that they possess. Some of the large and well known global firms in this sphere such as AC Nielsen, the SymphonyIRI Group etc. are well entrenched as part of the marketing philosophy in many, if not all, marketing and consumer goods businesses. Apart from these well known ones, a vast number of medium sized and smaller consulting firms offer a range of quantitative research assistance in many domains. The ABMS research community will be hugely benefitted if a sizable proportion of these consulting firms embody ABMS as part of their service offerings in a similar manner as other quantitative techniques. A change of mind set is required within this service industry so that adoption of ABMS technology happens organically – with the demand for agent based solutions going up on one hand, and solutions become increasingly available on the other. Hence, the research community should engage both sides of the market in a sustained manner – the consumer goods industry as well as the crucial service providers.

Two important qualifications to the points made above need to be made here. Firstly, this author is not advocating empirical methods *at the cost of* theoretical and interdisciplinary approaches – in fact quite the opposite. Robust empirical research is a *necessary* but not a sufficient precondition towards acceptability of ABMS within industries, businesses and quantitative practitioners. As pointed out succinctly in (Axelrod, 2006), agent based modelling acts as ”bridge” between disciplines, is able to tackle problems intractable through other methods and in spite of all its advantages, is more difficult to sell. Empirical research can be used to show that ABMS can not only tackle the same problems which have been normally addressed by traditional methodologies, efficiently, but can also extend the frontier by addressing issues fundamental to many disciplines and not tractable through traditional means. The state of the ABMS discipline has advanced very quickly where theoretical methods and addressing theoretical questions are concerned (and which is absolutely necessary in a nascent field), but it is now become necessary to address more empirical questions for broader acceptability of this area.

Secondly, there is no doubt that more and more data sets containing high quality disaggregated information are being made available and also will be available in the future. Computational data analysis/mining techniques such as machine learning, genetic algorithms etc. have improved and are able to search for complicated patterns and micro level relationships within data sets very efficiently. Hence, the question of the role of ABMS naturally arises in relation to these new methods of data analysis – and not just its position with regard to the traditional top down methods as has been discussed above. Most of these data intensive techniques tend to “dive into the data” blindly and are able to find interesting insights – they usually fall short of providing causal explanations behind the emergence of these patterns. It is here that ABMS has to play a crucial role – once again acting as bridge between the theory and the data – to provide an explanation of the patterns themselves. In fact, validation methodologies presented in (Sengupta and Glavin, 2010, 2012), involving agent specific parameter searches can be effectively achieved through optimization techniques – particularly, where large complicated parameter spaces have to be searched.

CONCLUSION

The ABMS paradigm has grown rapidly in the past decade within the research community and has just started making inroads into the business community as well. But the growth rate of the latter has been relatively low and thinly distributed. In particular, the inroads made into the mainstream marketing community in terms of actual implementation have been marginal. However, given the current practises in the industrial sector and the complexity seen in markets, it is here that ABMS can make the biggest impact in the future.

This paper sets out a few key areas where the social simulation community ought to invest more resources in the near future in order to encourage businesses to adopt this technology, side by side with the existing ones. These are: (a) improving the predictive capacity of ABMS technology within social systems, (b) build modelling capability to handle disruptive events for which past data is lacking or fragmentary, (c) engage the applied mathematics and computer science communities active in developing automated personalized algorithms for online markets and (d) help build more sophisticated but usable toolkits for the practitioners within businesses. At the same time, it specifies some strategies to adopt which would help researchers to align with the focus areas mentioned above. A lot more of empirically rooted modelling needs to forthcoming within research, concentrating on the verification and validation methodologies in ABMS. The underlying aim should be to bring the mainstream econometric modelling community within its fold. It is this research community which has the biggest impact in marketing and quantitative market research. These traditional modelling practises are driven forward, not only within the consumer goods businesses themselves, but also through the vast service industry which has grown up around it in the form of data providers and consultants. Hence to capture the attention of the practitioners within the industry, one would have to influence the big players in this sector as well.

Neither is the list of focus areas and strategies specified above exhaustive, nor does it claim to address all the requirements of researchers and practitioners in the field of ABMS. However, it is the author's belief that it is in these areas specified above, that a start can be made and which will maximize the chances of embedding social simulation methodologies within industry.

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