

Liquid Decision Making: An Exploratory Study

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ABSTRACT

Decision making is typically a well-defined process. The decision is formulated, the decision options are determined and information regarding the options is retrieved by the decision makers. Eventually, the decision is taken by some kind of voting. In this article we propose a novel approach to decision making called liquid decision making (LDM). LDM enables people to incorporate new information, to react to the voting of others, and to reconsider and revise their own voting. Additionally, a competitive element is introduced by basing the decision making mechanism on market principles: Indecision can lead to a loss of influence in the decision making. Artificial market perturbations are used to gauge the stability of a decision suggested by a market equilibrium. This article introduces LDM and its market perturbations and reports on an exploratory study conducted using LDM.

Categories and Subject Descriptors

H4.2 [Information Systems Applications]: Types of Systems—*Decision support*

General Terms

Experimentation

Keywords

Decision making, decision market, market equilibrium

1. INTRODUCTION

Imagine a group of people wanting to reach a common decision such as experts judging technological innovations or a panel deciding on directions of politics. Such groups ideally neither decide intuitively, spontaneously nor routinely. Rather, they need to aggregate information, consult among each other and react to the others' feedback. To address these needs, we propose an approach on the basis of market principles [10]. Markets have been attributed the ability

of efficiently aggregating information and representing it in the resulting price [7]. In our approach, people engage in a virtual market and trade shares according to their current opinion. The stocks in this market represent the single decision options that the participants have to decide upon. By buying shares they indicate their consent, by selling shares they express their disagreement with the respective decision options. High resulting prices indicate strong consent, low prices indicate dissent. We call our approach *liquid decision making* as it is characterized by its variable, asynchronous, distributed and collaborative nature. Participants are not restricted to a one-time voting on a fixed scale but rather are enabled to rethink their assessments and change their revealed preferences by trading accordingly. A web-based realization allows people to participate asynchronously and geographically distributed, thus extending their decision making phase beyond face-to-face meetings. The approach also provides immediate feedback to participants by calculating prices in real-time, thus increasing the collaborative experience. Market mechanisms also entail the property of a first-mover advantage. Those who buy early receive more stocks for their money as prices are lower. Those who are indecisive and buy at a later time, however, may lose influence on the decision making as stocks are more expensive.

Market principles were first applied to information aggregation by the Iowa Electronic Markets (IEM) in 1988. In this so called *prediction market*, participants forecast presidential election results in the U. S. by trading shares of this uncertain future event [4]. The single outcomes of the event are thereby represented as stocks on a virtual market and then traded by participants to indicate their assessment of the likelihood of the underlying outcome [12]. The resulting prices are interpreted as the aggregated forecast. Participants are rewarded for the accuracy of their individual forecasts. The more stocks they hold of the occurred outcome the more they are rewarded. This ability to aggregate information is also appealing for retrieving information on topics such as the selection of product concepts [3], the ranking of innovations [2] or the generation of ideas [9]. There, choice options are represented as stocks and traded by participants according to their assessments. The most discerning factor, however, is the missing external event that prediction markets consult for determining the forecasting accuracy and rewarding the participants [5]. The latter markets are therefore often called *preference markets*, as they aggregate the preferences of participants. For our approach, we employ the term *decision market* because of the decisions that are jointly reachable with it.

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Participants might have two different incentives for trading in a decision market. On the one hand, they might communicate their sincere assessments of decision options. On the other hand, they might seek to maximize their portfolio worth. Market organizers, however, are more likely to be interested in the communication of sincere assessments than in portfolio maximizers. After all, market organizers want to base further actions on the decision resulting from the market which should thus indicate what the participants really mean. In this article, we introduce the method of market perturbations for assessing these price formations resulting from different incentives. The general idea of market perturbations is to add artificial dynamics to market developments and observe their impact. As a first step in testing our approach, we executed an exploratory study to collect feedback from a small user group on usability of the software, on the application of market principles to decision making, on the decision options we chose for the study and to get qualitative experience with market perturbations.

The goal of most decision support systems is to support their users in formulating a decision problem and suitable options, generating supportive data to enable meaningful decisions and finally in selecting a decision option [11]. Consensus support systems aim at maximizing the degree of consensus among a group on a decision with a focus on properly mapping individual opinions to preference orders and on resolving objections [1]. In both cases, some kind of voting mechanism is employed to aggregate preferences and determine the final option. Liquid decision making poses an alternative to standard voting approaches as it combines both a form of concurrency inherent in markets and collaboration typical of group decisions. Besides its stand-alone usage, the authors argue that liquid decision making could also be integrated in the more extensive processes of decision support systems or consensus support systems, substituting their aspects of revealing, representing and aggregating preferences.

2. ASSESSING MARKET RESULTS

Benchmarking the outcomes of decision markets is not directly possible as the decision is yet to be made. In preference markets, the predominant solution is to either make up an artificial external judgement or to reward participants based on their portfolio worth. For decision markets, making up an artificial judgement is no option because participants of such a market would then try to predict this judgement. Thus, participants may be rewarded based on their portfolio worth. During the market, they may have at least two different kinds of incentives for trading. On the one hand, there is competitive trading for portfolio maximization. There, traders are likely to engage in what is known as a beauty contest [8]. They try to guess what the average trader will trade in and adjust their trading accordingly to make profits. In this case, market results report what the average trader thinks what the average trader will think of the market stocks. On the other hand, there is sincere revealing of participants' true opinions. Other applications of market principles for example to idea generation also report on the existence of such trading behaviors [9]. Traders may vary their portfolio maximization or preference revelation and thus a spectrum of market results should form.

A decision market organizer is interested in a decision of good quality, that is, the resulting market prices express what the participants really mean. For decision markets, we

define the quality of market results as follows. We consider a market result to be of poor quality if the resulting prices are based mostly on motivations such as portfolio maximization. We consider a market result to be of good quality if the prices are the result of mostly sincere trading. For assessing the quality of market results we develop a method for evaluating their quality and providing this information to both participants and organizers. The basis of our method are the reactions of traders to changes in market status. These changes could comprise changes of stock prices, available money or even tradable stocks. In the current status of our work, we focus on changing stock prices. The underlying assumption is that price changes stimulate different reactions of traders depending on their attitude towards the underlying decision option of the respective stock. We expect traders who sincerely favor a decision option to support this option even in the face of possible loss margins by either holding or buying additional shares of the respective stock. Contrariwise, we expect portfolio maximizing traders to limit their portfolio losses by selling shares of the respective stock.

Market Perturbations We propose to exogenously introduce market perturbations to induce the aforementioned price changes. At the same time, however, we design them in such a way that participants should not be able to discern these perturbations from trading actions of other participants. Currently, we focus on adding one or more artificial traders who perturbate stock prices by artificial sell or buy orders. The selection of stocks could be based on the level of their prices or on the volatility of their accompanying trading actions. In the exploratory study reported on in this article we focused on lowering high stock prices. An exemplary situation would be as follows. In a decision market, prices have leveled off at a certain point in time as traders bought and sold shares according to their respective goals in the market. Now, some market price changes due to trading actions of an artificial trader. The other traders are then likely to reconsider their current evaluations and their respective holdings of shares. Portfolio maximizing traders will check their overall portfolio worth and determine their current loss or profit margins. With decreasing stock prices they are likely to sell these stocks in order to limit losses. Sincere traders on the contrary check whether their favored stock is still adequately ranked. They are more likely to further support their favored stocks and either keep the perturbed stock or buy additional shares to further support their favored stock. In our approach, a market perturbation encompasses one or more perturbation actions which are the actual trading actions. More than one such perturbation action may be required to both stimulate traders and at the same time avoid disproportionately large trades.

We segment a perturbation as follows. In the selection step, we select a suitable stock for which all stocks of a given market are potential candidates. In our current design, the highest ranked stock is chosen for subsequent perturbation which remained in its equilibrium price for a duration at least as long as the average duration of the previous equilibrium phases. In the configuration step, we determine the number of shares to be traded by a fraction of the average price of all stocks in the market. Also, the artificial traders for actually performing the trade are chosen. In a market setting with around 5 participants, one artificial trader should be enough for unsuspectingly generating price movements. In larger settings, more artificial traders may

be necessary to generate price movements. In the execution step, one or more artificial traders perform the perturbation action. In the repetition step, we stop the perturbation if the perturbed stock reaches the price that existed prior to the perturbation or until a certain time elapsed. We determine this time by the average duration of the previous equilibrium phases of this stock.

3. MARKET EVALUATION AND RESULTS

We held two market sessions in a laboratory at our university for exploring our liquid decision making approach. We recruited the participants among university students and randomly selected 11 students for each session, with 7 and 11 showing up, respectively. Their task was to choose the most promising option from a list of innovations using our LDM approach. After an introduction to the approach and the software, participants traded for about 20 minutes without discussions being allowed. Then, they provided individual as well as group feedback. Every participant started with 5000 units of play money and no shares in his portfolio. We rewarded them based on their participation and not on market performance as not to over-emphasize competitive trading and portfolio maximization. The market employed the market maker mechanism invented by Robin Hanson [6] providing a trading intermediary that always accepts trading orders and adjusts market prices according to demand and supply. Participants do not trade directly with one another but with this intermediary, remedying the need of a matching counterpart for every trading action. Main results of our study are the formation of lively trading, the satisfactory application of liquid decision making to the joint identification of innovations and the successful execution of perturbations. The software was well accepted and the selected decision options deemed suitable. Below, we detail these findings and refer to the post-market survey with a Likert scale ranging from 1 (does not apply) to 5 (completely applies).

Decision Options We selected the decision options from the aerospace domain comprising a box wing aircraft, a modular passenger container aircraft, a super sonic aircraft, a blended wing body aircraft and an airship. For each of these options, we provided written information that participants read prior to trading. Completeness of this information was rated with a mean of 3.1 in accordance with the discussion feedback. It was commented that this information was not detailed enough for thoroughly judging the decision options. For further experiments, we will explicitly instruct participants that it will be sufficient to base their assessments on the given information and their background knowledge. Whether more common decision making topics would help participants in focusing on the market task is a matter of debate. The authors argue that it would be extremely difficult to construct a decision making topic for randomly chosen participants for which all of them have strong knowledge and preconceived opinions.

Market Application Participants lively traded shares of all stocks during both sessions of liquid decision making. A total of 182 and 437 trades were performed in sessions one and two, respectively. On average, traders of session one traded 26 times and in session two 43 times. Participants ranked the possibility of a continuous “voting” with a mean of 4.2, the immediate feedback of the pricing mechanism with 4.4 and the participatory nature with 4.0. They reported their satisfaction with the formation of the deci-

Table 1: Aggregation of individual rankings

	Session 1	Session 2
1.	Super Sonic	Box Wing
2.	BWB	BWB
3.	Box Wing	Airship
4.	Container	Container
5.	Airship	Super Sonic

sion result with a mean of 4.0. From these results, we think that the key features of liquid decision making, namely the continuous nature, the immediate feedback and its participatory approach, were understood and received very well by the participants. We thus argue that liquid decision making is a promising approach worth further studies. The aggregated rankings of the individual survey from both sessions are shown in Table 1. The market results of session one correspond to the individual ranking in places one, two and five, the results of session two completely concur with the individual ranking. The final market outcome of session one began to form about halfway into the market and in session two, the market outcome emerged right from the start of the market as is discernible in Figures 1 and 2. In session one, five minutes from the beginning of the market no distinct favorite option can be identified from the movement of prices. At around ten minutes into the market a preference for *Super Sonic* begins to form. This favorite then prevails for almost all the rest of the market duration. In contrast to session one, a head-to-head race forms early on between options *Box Wing* and *BWB* in session two. There, a clear separation is discernible between these two favorites and the remaining decision options. That is, participants clearly traded on two favorite decision options but were not able to finally resolve the head-to-head race. For our decision making approach, we think of the possibility of stopping such a race at a certain point in time and then transferring such multiple favorites to a subsequent market for final decision making.

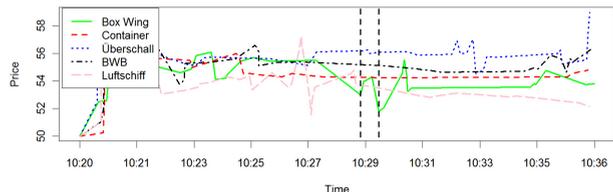


Figure 1: Prices of the first market session

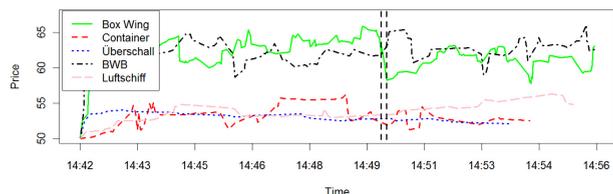


Figure 2: Prices of the second market session

Perturbations We executed the perturbation steps manually to be able to adapt their parameters to the reactions of traders. As pronounced equilibrium prices did not emerge, we selected the highest stock between half and two thirds

of the market duration and lowered its price by means of an artificial trader that was invisible to the other traders on the market tool. Considering the post-market discussion, no participant suspected this exogenous perturbation. In both sessions, the artificial trader twice sold 50 shares of stock *Box Wing*, as this was the highest stock at that time. The vertical dashed lines indicate the resulting prices (see Figures 1 and 2). In session one, the price level shortly recovered from this perturbation but remained lower for the rest of the market. In session two, correction to previous price levels did not occur, rather, the price level remained below. Following the perturbation, the head-to-head race continued in this session, but at lower price levels for decision option *Box Wing*. In this case, the perturbation was able to influence the head-to-head race but not to resolve it.

Trading Patterns We can discern trading patterns of buy-and-hold, head-to-head race and random in our study. The buy-and-hold pattern is characterized by a relatively short buying phase at the beginning and a following hold phase without any further trading. Such a participant is not very likely to change his portfolio because of market perturbations. However, this pattern exhibited only one of the ten participants of session two. With the head-to-head race pattern, two favorites were tried to be supported in turn. Two participants followed this pattern. Such participants should be more in favor of following a market perturbation. With the random pattern, the trading behavior seems more random without knowing the exact favorite or goal from the point of view of the market organizer. In decision markets, a sufficiently large portion of such traders should be susceptible to market perturbations.

Software We implemented our own web-based system to achieve the perturbation functionality. It provides information on available cash, portfolio worth, current rankings of decisions and participants and detailed information on trading options. For the experimenter, a view for monitoring all trading actions was provided. Participants reported ease of usage with a mean of 4.9 and intuitive navigation with a mean of 4.3. However, the statement “too many steps were necessary for executing a trading action” was rated with a mean of 2.7. Thus, we will collapse the two steps of selecting the stock and specifying the amount of shares into a combined step. Information on market activities was rated with a mean of 3.7. There, participants suggested to display more detailed information on transactions including purchase prices and currently liquidable loss or profit.

4. CONCLUSION AND FUTURE WORK

In this article, we introduced the approach of markets for decision making under the term *liquid decision making* and the application of market perturbations to identify different price origins and reported on a first exploratory study. The approach of liquid decision making was well accepted by the participants and a joint selection of a decision option was reached by lively trading. We executed the single steps of the market perturbations manually. For a beneficial application in decision making situations, we plan to automate the selection, configuration and execution of perturbations. As equilibrium prices hardly formed, we plan to extend our perturbation approach and account for such circumstances by leveling off the condition of equilibrium price formation. One possibility would be to introduce market perturbations to the highest stock in any case if a given time has elapsed

without the formation of an equilibrium price or to take further parameters into account such as the existence of a head-to-head race or general indecisiveness. Based on suggestions of participants, we will provide more detailed information on trades and liquidable profits as well as shorten the trading procedure in the market software. The goal of our initial exploratory study was not to quantitatively analyze the ability of perturbations to identify trader motivations. For further investigations, we thus plan for both a field study and a laboratory experiment. A field study serves for testing the approach over a longer period and in a distributed fashion. A controlled laboratory experiment targets to study the correlation of market perturbations and traders’ behavior.

5. REFERENCES

- [1] S. Alonso, E. Herrera-Viedma, F. Chiclana, and F. Herrera. A web based consensus support system for group decision making problems and incomplete preferences. *Information Sciences*, 180(23):4477 – 4495, 2010.
- [2] L. Chen, P. Goes, W. Harris, J. Marsden, and J. Zhang. Preference Markets for Innovation Ranking and Selection. *INTERFACES*, 40(2):144–153, 2010.
- [3] E. Dahan, A. Soukhoroukova, and M. Spann. New product development 2.0: Preference markets – how scalable securities markets identify winning product concepts and attributes. *Journal of Product Innovation Management*, 27(7):937–954, 2010.
- [4] R. Forsythe, F. Nelson, G. R. Neumann, and J. Wright. Anatomy of an experimental political stock market. *The American Economic Review*, 82(5):1142–1161, 1992.
- [5] A. Graefe. *Prediction Markets versus Alternative Methods - Empirical Tests of Accuracy and Acceptability*. PhD thesis, Institute of Information Systems and Management, Karlsruhe Institute of Technology, 2009.
- [6] R. Hanson. Logarithmic Market Scoring Rules for Modular Combinatorial Information Aggregation. *Journal of Prediction Markets*, 1(1):3–15, 2007.
- [7] F. A. Hayek. The Use of Knowledge in Society. *American Economic Review*, 35(4):519–530, 1945.
- [8] J. M. Keynes. *The General Theory of Employment, Interest, and Money*. Macmillan Cambridge University Press, 1936.
- [9] C. A. LaComb, J. A. Barnett, and Q. Pan. The imagination market. *Information Systems Frontiers*, 9(2-3):245–256, 2007.
- [10] S. Leutenmayr, F. Bry, T. Schiebler, and F. Brodbeck. Work in Progress: Do They Really Mean It? Assessing Decision Market Outcomes. In *Proceedings of 4. Workshop Digitale Soziale Netze im Rahmen der 41. Jahrestagung der Gesellschaft für Informatik (GI)*, Berlin, Germany, 2011.
- [11] J. F. Nunamaker and A. V. Deokar. GDSS Parameters and Benefits. In F. Burstein and C. Holsapple, editors, *Handbook on Decision Support Systems 1*, International Handbooks on Information Systems, pages 391–414. Springer Berlin Heidelberg, 2008.
- [12] J. Wolfers and E. Zitzewitz. Prediction Markets. *Journal of Economic Perspectives*, 18(2):107–126, Spring 2004.