Deductive and inductive data collection for agent-based modelling: A Dairy Supply Chain Case Study

Dhanan Sarwo Utomo, Bhakti Stephan Onggo, Stephen Eldridge

Department of Management Science, Lancaster University Management School, Lancaster LA1 4YX, United Kingdom

1 Introduction

This study compares the use of the deductive approach (questionnaire) and the inductive approach (role playing games) in the calibration of an agent-based model (ABM) and studies their effects on model validity and utility. ABM is a modelling methodology that puts emphasis on stakeholder behaviour (Samuelson, 2005). The validity of behavioural assumptions is critical in ABM because it increases the confident in the model for its use in decision making (Bendoly et al., 2006). Both quantitative and qualitative data collection methods have been used for ABM development (Robinson et.al, 2007; Yang & Gilbert, 2008). For example, Robinson et.al (2007) qualitatively compared the benefits of various data collection methods in eliciting stakeholder behaviour based on researcher experience. In our study, we make a quantitative comparison between deductive and inductive approaches by considering the following hypotheses:

- H1: When building a model for a system, inductive and deductive data collection may result in two different models
- H2: Inductive and deductive methods may have a different effect on model's external validity (i.e. when we compare them against secondary data).
- H3: Inductive and deductive calibration may produce ABMs with different internal validity (based on domain expert judgement).
- H4: Inductive and deductive calibration may produce different decision makers' utility toward the final model. (The model's utility indicates the level of confidence of the decision makers in using the model.)

2 Dairy Supply Chain Simulation Model

The case of the dairy supply chain in West Java, Indonesia, will be used to obtain empirical evidence to test the hypotheses. Prior studies have has shown that agricultural supply chains, such as dairy, are suitable to be modelled using ABM because they involve a number of stakeholders and each stakeholder has different production processes and decision making rules (Higgins et al., 2010). Furthermore, prior studies in this area (e.g. Krejci & Beamon, 2012) have enabled the development of initial model useful for our study. At the same time, milk is an important agricultural product in Indonesia and the sustainability of the local dairy industry is of real concern for government agencies (who will be involved in this study). There are many farmers who rely on milk-producing activities for their livelihood while the import of milk-related products is increasing due to a declining trend in domestic production (Daud et al., 2015). West Java province was selected because it is one of the biggest milk production centres in Indonesia and the headquarters of most of the institutions involved in this research are also located in this province which facilitates data collection.

The hypothetical model was developed based on the literature and field observation. This model covers the types of agents in the dairy supply chain (e.g. farmers, cattle traders, cooperative), the attributes of each agent (e.g. cash, number of cattle, cattle pen), and the decision making rules of each agent (e.g. decision when to sell or buy cattle). The objective of model is to investigate the impacts on milk quality and farmer's wealth of milk handling strategies adopted by the cooperative. Sensitivity analysis was used to conceptually validate the hypothetical model.

The hypothetical model will then be used to design the questionnaire and the role playing games. These two instruments will then be used to calibrate the decision making rules and mechanisms in the hypothetical model. The data collection process also aims to identify other mechanisms that were not incorporated in the hypothetical model. The target respondents in the survey and the players in the role playing games are stakeholders in the dairy supply chain. The same sets of respondents will participate in both data collection processes.

To test H1, the information obtained from both data collection processes will be compared. Based on this comparison, we will test whether different data collection processes can lead to two different models. We intend to quantitatively measure the differences using the distance ratio method (Markóczy and Goldberg, 1995; Schaffernicht and Groesser, 2011). This method has been used in system dynamics modelling to compare the difference between two model structures, but never been used in ABM.

Validation processes using secondary data have been widely used by ABM studies in agricultural supply chain (e.g. Schreinemachers et al., 2007). To test H2, after calibration, both simulation models will be initialized with the same set of inputs and run under the same set of parameters. Hence, the difference in the model outputs can be explained from the different mechanisms used in the models. Secondary data will be collected to validate the simulation models which includes data such as the average cattle live weight before slaughter (190.6 ± 39.6 kg in West Java province (Agricultural Data and Information Systems Center, 2012)). Statistical techniques (e.g. ANOVA and the t-test) will be used to test whether the two data collection processes for model calibration produce significantly different outputs and to identify which method that can produce more valid results.

To test H3 and H4, experts from universities and government agencies will be asked to justify the validity and utility of the simulation models. The experts are not involved in the survey and the role playing games. Hence, the bias that may occur due to the intervention carried out during the model calibration can be avoided (Schaffernicht and Groesser, 2011). These experts are also the potential users of the final model, thus they have enough credibility to justify the benefits of the model. The outputs and the mechanisms from both models will be presented to the human experts without revealing the calibration process. The experts are then asked to assess both models by using a questionnaire. This will enable us to conduct statistical analysis on the experts' perception towards the two models.

Specifically, to test H3, the experts will be asked to perform three assessments as described by Klügl and Bazzan (2012):

- Animation Assessment: The human experts assess whether the animation of the overall simulated system (or of parts of it) in ABM appears to behave like the dairy supply chain that is being studied.
- Output Assessment: The human experts are asked to compare the simulation outputs and their experience with the models. There are several aspects that can be assessed by the experts *i.e.* absolute values, relations between different values and also the dynamics and trends of the different output values of simulation runs.
- Immersive Assessment: A human expert looks through the eyes of one particular agent and sees what the agent perceives and how it reacts on it. Based on this information the experts can evaluate directly whether the behaviour of the simulated agent is appropriate.

To test the H4, the experts will be asked to assess five basic dimensions of a model's value for its users based on the criteria of King and Rodriguez (1981):

- Use: The probability that the decision makers will use the simulation to analyse policy scenarios, after evaluating the mechanisms and the behaviour of the simulation.
- Other: The probability that s(he) will recommend the simulation to other decision makers, after evaluating the mechanisms and the behaviour of the simulation.
- Success: The perceived probability that the simulation can produce good policy.
- Worth: The decision maker's evaluation of the worth of the simulation.
- Accuracy: The level of accuracy that they can expect from the simulation.

3 Summary

This study is expected to produce insight on the effects of different data collection methods toward model's validity and utility. The data collection methods have been used in another simulation paradigm (i.e. system dynamics) and similar effects may be observed. In system dynamics, the effects of different model development process toward users understanding and their ability to make decision have been extensively studied (e.g. Langley and Morecroft, 2004; Borštnar et al., 2011; Gary and Wood, 2011). To our knowledge, the same study has not been done for ABM. Furthermore, a practical contribution of this study is the enabling of the analysis of policy scenarios that may support the sustainability of dairy industry in Indonesia.

References

1. AGRICULTURAL DATA AND INFORMATION SYSTEMS CENTER 2012. Survei Karkas Sapi Potong dan Kerbau Tahun 2012. Newsletter Pusdatin.
2. BENDOLY, E., DONOHUE, K. & SCHULTZ, K. L. 2006. Behavior in operations management: Assessing recent findings and revisiting old assumptions. Journal of Operations Management, 24, 737-752.
3. BORŠTNAR, M. K., KLJAJIĆ, M., ŠKRABA, A., KOFJAČ, D. & RAJKOVIČ, V. 2011. The relevance of facilitation in group decision making supported by a simulation model. System Dynamics Review, 27, 270-293.
4. DAUD, A., PUTRO, U. & BASRI, M. 2015. Risks in milk supply chain; a preliminary analysis on smallholder dairy production. Livestock Research for Rural Development, 27, 137.
5. GARY, M. S. & WOOD, R. E. 2011. Mental models, decision rules, and performance heterogeneity. Strategic management journal, 32, 569-594.
6. HIGGINS, A. J., MILLER, C. J., ARCHER, A. A., TON, T., FLETCHER, C. S. & MCALLISTER, R. R. J. 2010. Challenges of operations research practice in agricultural value chains. Journal of the Operational Research Society, 61, 964-973.
7. KING, W. R. & RODRIGUEZ, J. I. 1981. Note PARTICIPATIVE DESIGN OF STRATEGIC DECISION SUPPORT SYSTEMS: AN EMPIRICAL ASSESSMENT. Management Science (pre-1986), 27, 717.
8. KLÜGL, F. & BAZZAN, A. L. C. 2012. Agent-Based Modeling and Simulation. AI Magazine, 33, 29-40.
9. KREJCI, C. C. & BEAMON, B. M. Modeling food supply chains using multi-agent simulation. Simulation Conference (WSC), Proceedings of the 2012 Winter, 9-12 Dec. 2012 2012. 1-12.
10. LANGLEY, P. A. & MORECROFT, J. D. W. 2004. Performance and learning in a simulation of oil industry dynamics. European Journal of Operational Research, 155, 715-732.
11. MARKÓCZY, L. & GOLDBERG, J. 1995. A method for eliciting and comparing causal maps. Journal of Management, 21, 305-333.
12. ROBINSON, D. T., BROWN, D. G., PARKER, D. C., SCHREINEMACHERS, P., JANSSEN, M. A., HUIGEN, M., WITTMER, H., GOTTS, N., PROMBUROM, P. & IRWIN, E. 2007. Comparison of empirical methods for building agent-based models in land use science. Journal of Land Use Science, 2, 31-55.
13. SAMUELSON, D. A. 2005. Agents of Change. OR/MS Today. February ed. Marietta: Informs.
14. SCHAFFERNICHT, M. & GROESSER, S. N. 2011. A comprehensive method for comparing mental models of dynamic systems. European Journal of Operational Research, 210, 57-67.
15. SCHREINEMACHERS, P., BERGER, T. & AUNE, J. B. 2007. Simulating soil fertility and poverty dynamics in Uganda: A bio-economic multi-agent systems approach. Ecological economics, 64, 387-401.
16. YANG, L. U. & GILBERT, N. 2008. GETTING AWAY FROM NUMBERS: USING QUALITATIVE OBSERVATION FOR AGENT-BASED MODELING. Advances in Complex Systems, 11, 175-185.