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Using agent-based simulation to explore sugarcane supply chain transport complexities at a mill scale

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Abstract

The sugarcane supply chain (from sugarcane grower to mill) have particular challenges. One of these is that the growers have to deliver their cane to the mill before its quality degrades. The sugarcane supply chain typically consists of many growers and a mill. Growers deliver their cane daily during the milling season; the amount of cane they deliver depends on their farm size. Growers make decisions about when to harvest the cane, and the number and type of trucks needed to deliver their cane. The mill wants a consistent cane supply over the milling season. Growers are sometimes affected long queue lengths at the mill when they offload their cane.

A preliminary agent-based simulation model was developed to understand this complex system. The model inputs a number of growers, and the amount of cane they are to deliver over the milling season. The number of trucks needed by each grower is determined by the trip, loading and unloading times and the anticipated waiting time at the mill. The anticipated waiting time was varied to determine how many trucks would be needed in the system to deliver the week's cane allocation. As the anticipated waiting time increased, the number of trucks needed also increased, which in turn delayed the trucks when queuing at the mill. The growers' anticipated waiting times never matched the actual waiting times. The research shows the promise of agent-based models as a sense-making approach to understanding systems where there are many individuals who have autonomous behaviour, and whose actions and interactions can result in unexpected system-level behaviour.

Key words: Agent-based simulation, sugarcane supply chain, transport, queue.

1 Introduction

A supply chain is formed when different business entities co-operate to source raw materials, manufacture finished products and deliver these products to the market (Beamon,

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1998). Materials flow forwards in the chain, and information (*e.g.* about how much of the material needs to be sent to the next entity, and production rates) flow backwards up the chain (Beamon, 1998). The demand for materials from the downstream business helps the upstream business to adapt to the rate of flow of materials in the chain as a whole (North & Macal, 2007).

The supply chain environment can be described as complex in terms of detail, with many variables which are interconnected; it is also complex from the point of view of the chain's dynamics, in that the variables are related in a non-linear way, with time delays, which makes cause-effect relationships more difficult to identify (Größler & Schieritz, 2005). For example, a participatory simulation game called the Beer Game (Sterman, 1989) was invented to show students the complexities and adaptive nature of the supply chain environment. In this game, the market demand was kept constant for a number of time periods to enable the participants to get to know the game and develop ordering rules. The demand was then doubled for the remainder of the time periods in the game. After the sudden doubling of the demand, it was found that the rest of the chain struggled to adapt the quantity of materials to send to the next stage in the chain, irrespective of how long the game continued (North & Macal, 2007).

Agricultural supply chains are those in which the raw material is gained as a result of a farming activity (Higgins *et al.*, 2010). They have more challenges than other manufacturing supply chains (Higgins *et al.,* 2007; Higgins *et al.*, 2010). They typically have thousands of participants rather than a few participating firms; in addition to responding to differing market demands, they are subject to uncertainties in weather and climate change (Higgins *et al.*, 2010).

The sugar supply chain is an agricultural supply chain with two parts: the sugarcane supply chain (where sugarcane is taken to the mill to be crushed) and the distribution chain for the stabilised raw sugar crystals (Bezuidenhout *et al.,* 2012). The first part of the sugar supply chain is of particular interest, because of the complexities outlined above in terms of the climatic environment, and because of the large number of role players. For example, one such sugarcane supply chain in KwaZulu-Natal had over 1000 participants (Le Masson, 2007). By contrast, after processing the sugarcane, the raw sugar belongs to one company, which is responsible for distributing it to its markets (Bezuidenhout *et al.,* 2012).

The sugarcane supply chain's role players consist of growers, harvesters, transporters, the mill and the Mill Group Board (Bezuidenhout *et al.,* 2012), which co-ordinates the supply chain and ensures a consistent supply of sugarcane to the mill during the milling season. A number of growers typically supply cane to one mill. Many of the growers transport their own sugar cane to the mill, whereas others use the services of contracted hauliers. During the 38-week long milling season, the growers need to deliver their cane to the mill as fast as possible after it has been harvested, as the sugarcane's quality declines thereafter. To ensure a consistent supply to the mill, growers deliver their cane daily. Among the problems faced by growers delivering their sugarcane to the mill are long queues at the mill area. If the growers have delivery problems, the mill could be starved of cane, which causes processing problems for the mill.

During one milling season, there are many interactions between similar and different types of role players, and also the environment and the role players (for example, the onset of rainy weather could cause the sugarcane supply chain to work differently from how it works in fine weather). These interactions can have system-wide impacts which are difficult to explain from a local understanding of the role players and their actions. In addition, the relationships (and interactions) between the role players are not static for the whole milling season.

The aim of this research is to create a computational framework for the simulation and modeling of the sugarcane supply chain. The framework approaches the supply chain in a bottom-up way, so that the system-level effects of individuals' actions and interactions (such as queues at the mill, the delay between when the cane is harvested and crushed at the mill, and number of hours in which the mill is starved of cane) can be explored further.

2 Literature review

Owen *et al.* (2010) have identified three main ways of simulating supply chains: using System Dynamics, discrete event simulation models and agent-based modelling. System Dynamics models use a top-down approach to modelling, and the resultant models tend to be "highly aggregated, high-level" representations of the processes and flows in a system (North & Macal, 2007). These types of models assume that the processes do not change over time, and the ways in which the entities in the model relate to each other is static. Discrete event simulation models focus on processes and events which occur during the lifetime of the process (North & Macal, 2007). Like System Dynamics models, discrete event simulation models also assume fixed processes and interrelationships at the start of the simulation period (North & Macal, 2007). In these models, there is a single thread of control (Siebers *et al.*, 2010). Agent-based modelling, on the other hand, uses a bottom-up approach and caters for heterogeneous entities (called agents). This approach also assumes that relationships between the agents are not static in the lifetime of the model (North & Macal, 2007), and that control is decentralised since the agents behave independently of each other (Siebers *et al.*, 2010). Since there are many different types of decision-makers in the sugarcane supply chain, and each decision maker could have a different approach to making decisions, the agent-based modelling and simulation approach is better for modelling the complex dynamics of the supply chain.

Over recent years, several authors have developed simulation models of sugarcane supply chains. In Australia, Thorburn *et al.* (2005) created an agent-based model of regional sugarcane value chains to determine the wider impacts of implementing or increasing the electricity co-generation capacity in the chain. In their model, an agent represented the different supply chain sectors. As a result of the study, in one region, maximising electricity co-generation was abandoned because of the negative agronomic impact of this option. Le Masson (2007) developed a discrete event simulation of a KwaZulu-Natal sugarcane supply chain. This work revolved around testing the impacts of mechanical harvesting on the logistical supply to the mill – to see if the milling season length could be reduced. The simulation worked on a weekly basis (Le Gal *et al.,* 2009). McDonald *et al.* (2008) also developed a discrete event simulation of the same mill area as Le Masson (2007)'s work

Grower no.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Distance to mill	3	3	4	5	5	6	7	9	10	13	13	13	13	16	16	16	17
Grower no.	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
Distance to mill	19	20	20	20	21	22	23	24	25	27	27	30	33	36	36	37	42
Grower no.	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	
Distance to mill	43	43	44	47	48	48	48	50	52	54	54	55	55	57	57	58	

Table 1: *Grower distances to mill (in km).*

on an hourly basis, including spiller and bundle cane. Simulation models of the sugarcane supply chain which modelled at time steps of under one hour were not found.

3 Methodology and model development

An initial analysis of the sugarcane supply chain domain was carried out. This included visiting two different South African sugar mills, speaking to domain experts and reviewing published literature (articles and theses). The analysis showed that growers, hauliers (truck drivers) and the mill (including the weighbridge and mill yard) were the main role players and these became agents in the model. The analysis concentrated on what decisions the role players made and how the decisions were made.

An iterative model implementation approach was followed, as is recommended for developing agent-based simulations (North & Macal, 2007). The first iteration implemented a restricted list of features. More features were implemented in subsequent iterations of the model. After each iteration, the model was tested to ensure that the features were working as expected before proceeding to the next iteration. The model was developed in the Repast Symphony platform (North *et al.*, 2013).

The current model respresents the workings of a single sugar mill and the growers and hauliers which supply it. It models the activities of the grower, haulier and mill every minute. In this model, each grower uses his own truck(s) to take the cane to the mill. The model uses similar input data (number of growers, their distance from the mill) to that of a KwaZulu-Natal sugarcane supply chain (Le Masson, 2007; McDonald *et al.*, 2008; Le Gal *et al.*, 2009). There are 50 growers which supply sugarcane to the mill (see Table 1).

The growers and hauliers work in daylight hours (6am to 6pm), Monday to Saturday, whereas the mill works 24 hours per day, seven days per week. Only growers who bundle their cane into 9 tonne bundles before transporting it to the mill are considered in this model. (The growers which transport their cane loose and then spill it onto the infeed conveyer belt at the mill have been ignored in this version.) Growers which are less than 18 km away from the mill use trucks which are configured to transport three bundles per trip, whereas those which are further away are configured to transport four bundles per trip.

In the model, each of the 50 growers has to deliver 38 000 tonnes of cane during the 38-week milling season (*i.e.* they have to deliver a weekly allocation of 1 000 tonnes, or a daily allocation of 166.66 tonnes). The grower calculates how many trips are needed, and

Grower no.	No. of trips needed per week	No. of bundles per trip	No. of bundles to make (weekdays)	No. of bundles to make (Saturday)	Max. tonnes to deliver weekly
1 to 17	3	38	21	9	1 026
18 to 50	4	28	20	12	1 008

Table 2: *Weekly grower delivery targets.*

rounds up the number of bundles to suit his transport configuration (to avoid partially empty loads). Based on the number of bundles to be made, the grower ensures that the cane for the day's trips is bundled and ready for transport by 6am. Table 2 shows these details for the growers.

At the beginning of the simulation, each grower calculates the cycle time (time to make a round trip) to determine the number of trucks needed to transport the week's allocation. The cycle time (in minutes) is calculated by

$$\begin{aligned} Cycle\ time\ =& loading\ time + trip\ time\ to\ mill + weighbridge\ time + waiting\ time\ at\ mill \\ & + unloading\ time + \ trip\ time\ to\ farm \end{aligned}$$

where *loading time* = 12 mins; *trip time to mill* = travel time at 40km/hr; *weighbridge time* = 2 mins; *waiting time at mill* = growers' anticipated wait at the mill (this value was varied for each simulation run); *unloading time* = 4 mins; *trip time to farm* = travel time at 45km/hr.

The actual waiting time at the mill depends on the number of trucks in the queue. The cycle time is used to determine how many trucks each grower needs to deliver the week's cane allocation.

The simulation model was initially run for a two week period with the grower distances to the mill as shown in Table 1, but with only one truck per grower. In this run, there was an ample supply of cane. Each grower had to deliver 1 000 tonnes of cane weekly. This output gave a baseline of the maximum tonnes which a grower can deliver with one truck. All growers underdelivered, and could not complete the required number of trips (see section 4 for the results of this run). The model was then changed to allow growers to have as many trucks as were needed to deliver the week's allocation. The grower also bundled the daily allocation of cane at 6am. The cycle time for each grower was then calculated. If a grower had more than one truck, the trucks would start to load cane and then leave the farm in a staggered fashion described by

$$Time\ for\ i^{th}\ truck\ to\ start\ loading = 6am + (cycle\ time) * \frac{(i-1)}{no.\ \ of\ trucks}$$

Thirteen two-week long runs were performed to analyse the effect of changing the *waiting time at mill* component of the cycle time formula. The *waiting time at mill* was incremented in steps of 30 mins from 0 mins to 360 mins. The results for the second of the two weeks were analysed, since the hauliers were still learning the average trip time in the first week.

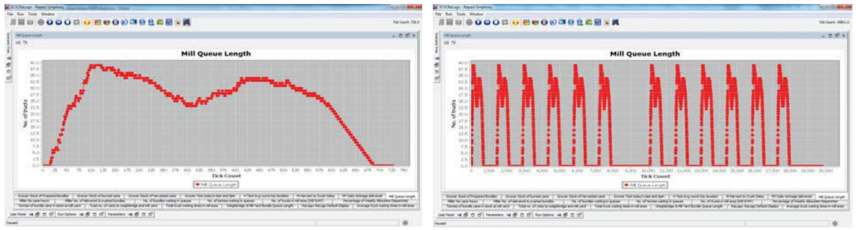

Figure 1: *Model output: queue length at the mill for Monday of the first week (left) and for two weeks (right). The growers deliver cane six days a week, Monday to Saturday.*

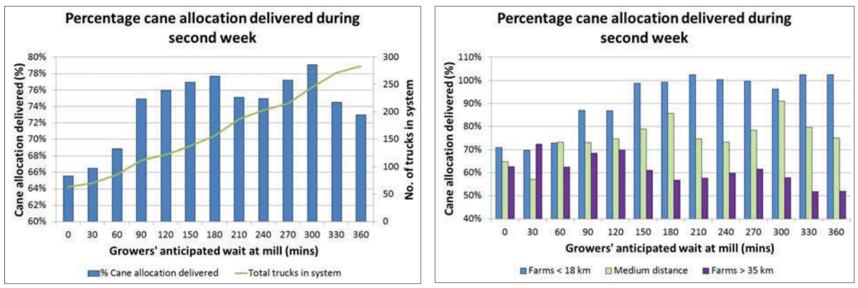

Figure 2: *Percentage cane allocation delivered during the week: for all the growers supplying the mill (left) and broken down by distance category (right).*

4 Results

The model first simulated the supply chain for two weeks, with ample cane supply. Each grower only had one truck with which to deliver the cane to the mill. None of the growers were able to supply the full 1 000 tonnes required for the week. The three growers within a 4 km radius of the mill were able to deliver 97.2% of their weekly allocation, while the growers between 47 and 58 km from the mill were only able to deliver 43.2% of their weekly allocation. On average only 63.9% of the week's cane allocation was delivered.

For this run, each day's cumulative deliveries was compared for weeks 1 and 2. The results were identical except for growers 35 and 36 (both 43 km from the mill). For these growers, the order of joining the queue made a difference to the number of trips they could make that day.

Figure 1 shows model output for this run for the queue at the mill for the first day (Monday) and for two weeks, starting on Monday. As can be seen, the queue length at the mill is very similar each day. Those familiar with truck queues at the mill have remarked that it is common to have a double hump in the mill queue, as shown here. The first truck arrives at 6:15. The first hump has its maximum between 7:39 and 8:00. The second hump is between 12:52 and 13:44. The last truck leaves the mill area at 17:25. The model was then changed so that growers would prepare enough cane for the day's trips at 6am, and each grower had as many trucks as he needed, based on the cycle time. The *waiting time at mill* component of the cycle time was varied from 0 to 360 mins in steps of 30 mins.

The results (Figure 2) show that even though more trucks were added, the growers were unable to deliver the full cane allocation for the week for any of the 13 anticipated waiting

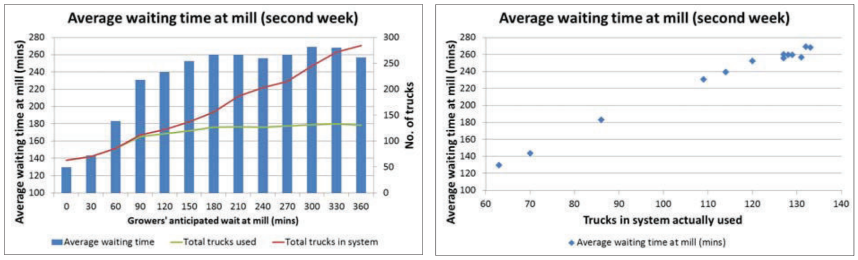

Figure 3: *Average waiting time at mill for each anticipated wait at mill run (left), and plotted by actual trucks used (right).*

times. At 300 minutes anticipated waiting time, the maximum of 79.1% of the total week's allocation was delivered. At 180 minutes, the next highest delivery rate of 77.7% was achieved. Figure 2 also shows the percentage allocation delivered for farms close to the mill (under 18 km), those far from the mill (greater than 35 km) and those farms lying in between. As the growers' anticipated waiting time increased, the farms close by and a medium distance away were better able to deliver.

Figure 3 (left) shows the average truck waiting time at the mill for each of the growers' anticipated waiting times. It shows that the growers were unable to anticipate the actual waiting time at the mill, since the other growers were also adding trucks to the system, causing the queues (and therefore the actual waiting time) to be longer. It was found that although the growers were adding trucks to the system, for anticipated waiting times of 90 minutes and longer, not all of them were being used. This is because the staggered leaving time formula used prevented some of the trucks from leaving earlier: when it was their time to leave, they found they could not get back to the farm by 6pm, so did not leave at all. When plotting the actual waiting time at the mill by the number of trucks actually used to deliver cane (Figure 3 right), the graph shows a linearly increasing trend.

5 Discussion

When growers used only one truck each, only 63.9% of the cane was delivered; using more than one truck increased growers' ability to deliver (they delivered between 66.6% and 79.1% of the week's allocation). Alternatives for the "truck leaving time" rule need to be investigated.

Le Gal *et al.* (2009, pg 171) report that with 195 trucks (considered "severely over-fleeted"), the wait at the mill can be 2 hours. In addition, between 2001 and 2006, the mill only managed to crush 76% of the allocation due to cane supply shortages and mill breakdowns. Our model shows that at 2 hours, the allocation delivered would also be 76%, but with fewer trucks (122 were created and 114 were used). This may be due to the fact that in our model, growers have exactly the same allocation, whereas in reality, their allocation would vary depending on the farm size and growth rate *etc.* Our model also does not take into account spiller cane deliveries. McDonald *et al.* (2008) also report that the waiting time in the mill yard is about 2 hours for 105 trucks. It should be noted that these two studies simulated a more realisitc grower allocation distribution, and they also modelled both bundle and spiller cane deliveries.

The agents in this simulation (growers and hauliers) all followed the same rules of behaviour. Even so, the results are a useful indication of how the behaviours of individual autonomous agents (role players) can affect the system's behaviour.

6 Conclusions and future work

This model gives a starting point for being able to explore sugarcane supply chain complexities. For example, using a non-agent-based approach, it is difficult to determine at the individual level (grower) the effect of adding more trucks to the system (represented by the mill queue) because of the system feedback: adding more trucks increases the waiting time in the queue at the mill. This model has shown the benefit of the bottom-up approach to modelling the mill queuing time as an emergent system effect, rather than using it as an average model input.

Using the agent-based modelling approach opens opportunities for varying agents' behaviour, modelling groups of growers, changing weather conditions, *etc.* to investigate the system-wide effects. In future, the model will be used to investigate other truck leaving time rules. The model's functionality will also be extended to include spiller growers and expand the decision-making behaviour of the agents.

7 References

Beamon, B., 1998. Supply chain design and analysis: models and methods. *International Journal of Production Economics,* 553, pp. 281-294.

Bezuidenhout, C., Bodhanya, S. & Brenchley, L., 2012. An analysis of collaboration in a sugarcane production and processing supply chain. *British Food Journal,* 1146, pp. 880-895.

Größler, A. & Schieritz, N., 2005. Of stocks, flows, agents and rules - "strategic" simulations in supply chain research. In: H. Kotzab, S. Seuring, M. Müller & G. Reiner (Eds). *Research methodologies in supply chain management.* Heidelberg: Physica-Verlag, pp. 445-460.

Higgins, A. *et al.*, 2010. Challenges of operations research practice in agricultural value chains. *Journal of the Operational Research Society,* 616, pp. 964-973.

Higgins, A., Thorburn, P., Archer, A. & Jakku, E., 2007. Opportunities for value chain research in sugar industries. *Agricultural Systems,* 943, pp. 611-621.

Le Gal, P.-Y., Le Masson, J., Bezuidenhout, C. & Lagrange, L., 2009. Coupled modelling of sugarcane supply planning and logistics as a management tool. *Computers and Electronics in Agriculture,* 682, pp. 168-177.

Le Masson, J., 2007. *Articulation de modèles de planification logistique et d'approvisionnement d'une sucrerie: application à la mécanisation de la récolte de canne dans le bassin de Noodsberg (Afrique du Sud),* Masters thesis, Montpellier, France: AgroParisTech - Cirad.

McDonald, B., Dube, E. & Bezuidenhout, C., 2008. *Modelling and simulation for analysis of sugarcane transport systems.* Proceedings of the Second IASTED Africa Conference Modelling and Simulation (AfricaMS 2008), pp. 247-253.

North, M. *et al.*, 2013. Complex adaptive systems modeling with Repast Simphony. *Complex Adaptive Systems Modeling,* http://www.casmodeling.com/content/1/1/3 [accessed 15-5-2014].

North, M. & Macal, C., 2007. *Managing business complexity: discovering strategic solutions with agent-based modelling and simulation.* New York: Oxford University Press, Inc.

Owen, M., Albores, P., Greasley, A. & Love, D., 2010. *Simulation in the supply chain context: matching the simulation tool to the problem.* Proceedings of the 2010 Operational Research Society Simulation Workshop (SW10), pp. 229-242.

Siebers, P. *et al.,* 2010. Discrete-event simulation is dead, long live agent-based simulation!. *Journal of Simulation,* 43, pp. 204-210.

Sterman, J., 1989. Modeling managerial behavior: misperceptions of feedback in a dynamic decision making experiment. *Management Science,* 353, pp. 321-339.

Thorburn, P. *et al.*, 2005. *Integrated value chain scenarios for enhanced mill region profitability. Final report to the Sugar Research and Development Corporation on SDRC Project CSE010.,* Sugar Research and Development Corporation, Australian Government.

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