AN OPTIMAL CANE DELIVERY SCHEDULING APPROACH

Surya Prakash[1,2]
Anjeela Jokhan[1]
[1]University of the South Pacific, Fiji
[2]University of Canberra (Adjunct), Australia

1. INTRODUCTION

Decreasing the cost of transporting sugar cane to mills is of paramount importance to all sugar producing industries since it usually is a major portion of the total cost of sugar cane operations.

Transportation of sugar cane from farms to mills is mostly done predominantly by road with rail also utilised. For road transportation mode, when sugar cane on the farm is harvested, it is transported to the designated mills by either farm-owner acquired lorries or hired ones or the lorries dispatched by the milling operators. A non-optimal schedule or no schedule of cane delivery leads to increased costs associated with either idle mill time or wait/queue time of the lorries or both.

If the arrival times of the lorries were scheduled, taking into consideration different travel times to the mills from various locations, the processing time at the mills and the time taken to cut cane and load lorries at the farms, the cost due to idle mill time and/or wait/queue time of the lorries could be reduced even totally eliminated.

Scheduling of sugarcane delivery has received some attention beginning with (Abel 1981) who was the first to develop a railway scheduling model. This model was later transformed by (Pinkney and Everitt 1977) into a user friendly application. In relation to scheduling of road transportation of sugar cane, (Hansen et al. 2001) attempted the scheduling process by simulation. (Milan et al. 2003) developed linear programming model for pickup of canes from various farms and storage locations to minimise costs, accounting for more than one mode of transportation. (Higgins 2006) developed a model to schedule road transport using meta-heuristics and tabu search to find solutions.

This paper focusses on using the Monte Carlo approach to road transportation scheduling of cane delivery and presents a Monte Carlo scheduler that minimizes mill idle time as a first criterion with lorry queue time as the next, while incorporating variables such as different travel times to the mills from various locations, the processing time at the mills and the time taken to cut cane and load lorries at the farms.

2. MONTE CARLO SIMULATION

Monte Carlo simulation is a computerized mathematical technique that approximates solutions to quantitative problems through statistical sampling. The technique is used by professionals in fields such as finance, project management, energy, manufacturing, engineering, research and development, insurance, oil & gas, transportation, and the environment. This method is useful for obtaining numerical solutions to problems which are too complicated to solve analytically.

Monte Carlo simulation furnishes the decision-maker with a range of possible outcomes and the probabilities of the possible outcomes. The technique was first used by scientists working on the atom bomb (Kochanski 2005).

Monte Carlo simulation involves building models of possible results by substituting a range of values with a probability distribution for any factor that has inherent uncertainty. It then calculates results repeatedly, each time using a different set of random values from the probability functions. The results of Monte Carlo simulation are not single values but distributions of possible outcome values (Vose 2008).

3. MODEL FORMULATION

The scheduling problem for sugarcane road transport involves scheduling of vehicles (lorries) to arrive at the mill from various locations. We will assume the scenario that these vehicles start their journey from the cane farms where they get laden with cane from a particular location and travel straight to the mill. This is unlike the scenario used in (Higgins 2006) where the vehicles leave the mill to pick up several trailers before returning to the mill. For the road scheduling problem discussed in this paper, a good solution is characterised by minimal mill stoppage time and minimal waiting time for arriving vehicles at the mill. Since mill stoppage is costlier than the queueing time, priority is given to reducing mill stoppage after which queueing time is minimised.

To demonstrate Monte Carlo scheduling approach:

Suppose there are n locations $(L_1, L_2, L_3, L_4, L_5, \ldots\ldots, L_n)$ from which cane has to be delivered to a mill. These locations are at various distances away

$(d_1, d_2, d_3, d_4, d_5, \ldots\ldots, d_n)$ from the mill and as such the time taken $(t_1, t_2, t_3, t_4, t_5, \ldots\ldots, t_n)$ for a cane truck to reach the mill from each of these locations would vary. The quantity of cane at each location available is $(Q_1, Q_{2,} Q_3, Q_4, Q_5, \ldots\ldots, Q_n)$ tonnes of cane with as many trucks needed to transport cane to the mill as needed. Each truck has a capacity to carry 10 tonnes of cane. Assume that the crushing rate of the mill is denoted by $\mathrm{Crushing\_Rate}$ in tonnes/hr.

If $x < Q$ tonnes of cane is needed to be crushed, what would be the best combination of deliveries from $(L_1, L_2, L_3, L_4, L_5, \ldots\ldots, L_n)$ such that mill idle time is minimised as a first criterion with minimisation of lorry queue time as the next?

To use the Monte Carlo approach, we treat this as a "Truck Service queue" problem whereby cane trucks arrive at random times. If the mill is not processing another truck, an arrival goes directly into processing and spends no time in queue. But if the mill is processing another, the arrival joins the end of a queue, from which trucks are processed on a first-come-first-served order. The system starts at time 0 and idle (no trucks present) and continues until $x < Q$ tonnes of cane have arrived. The input distribution used is a discrete function (see Figure 1 shown when n = 5) such that the probability of choosing a cane laden truck from any location $(L_1, L_2, L_3, L_4, L_5)$ is the same.

Each Monte Carlo iteration randomly selects 1 location from each of the locations as many times as required to satisfy the value of x and evaluates the mill wait time and the queue time of the trucks for each combination. The results generated are the probability distributions of mill wait time and the queue time of trucks.

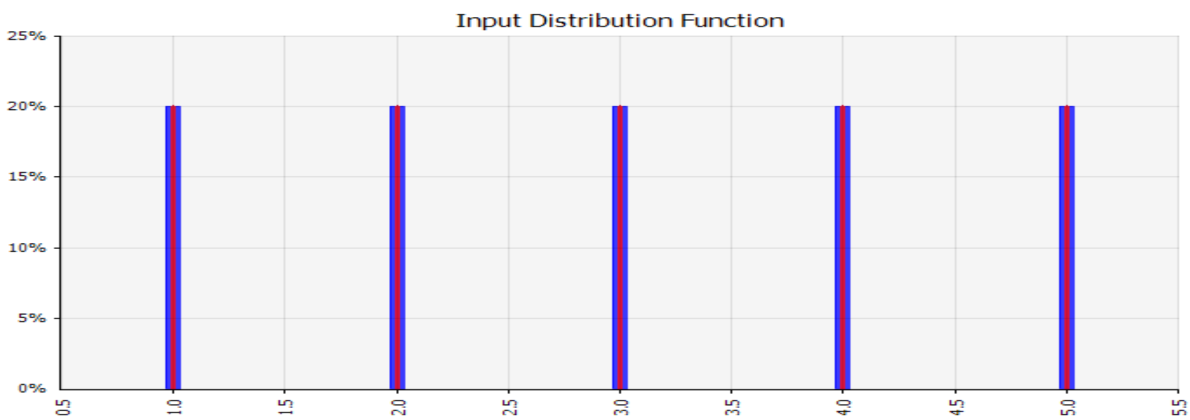


Figure 1: Input Distribution Function

4. MODEL SOLUTION

To demonstrate our Monte Carlo approach, two scenarios were chosen, both with made up data: one being a simplified version and the other with some complexities included.

4.1. Scenario 1

Let's consider a simple approach with 5 locations (n = 5) with the following quantities:

Table 1: Input variables to Monte Carlo simulation

Location	L_1	L_2	L_3	L_4	L_5
Distance (km)	30	60	100	150	200
Cane Quantity (tonnes)	2000	2000	2000	2000	2000
Time taken (hrs) to travel to mill*	0.5	1	1.67	2.5	3.33

*Assuming that all trucks travel at 60km/h

Assume that Crushing_Rate is 84 tonnes/hr, the number of tonnes to be crushed, x = 1000 tonnes and the time taken to cut and load cane onto a truck is 60 minutes. This implies that, to satisfy, $x = 1000$, we need 100 trucks carrying 10 tonnes of cane from any of these 5 locations.

Note that: When the time taken to cut and load a truck is taken into consideration, this implies that if truck A leaves location, L_1 at time t, the next truck, B will leave L_1 after 60 minutes. Thus the difference in arrival at the mill, after 30 minutes of travel time each, of trucks A and B is 60 minutes.

Each Monte Carlo iteration randomly selects 1 location from each of these 5 locations 100 times and evaluates the mill wait time and the queue time of the trucks for each combination. The reason for the 100 is because that is the number of trucks needed to fulfil the requirement as per the value of x. All chosen locations start cutting and loading canes on trucks at the same time and stop when the required set quota is reached.

The results of a simulation with 50000 iterations are as below:

Figure 2: Distribution of Mill idle time

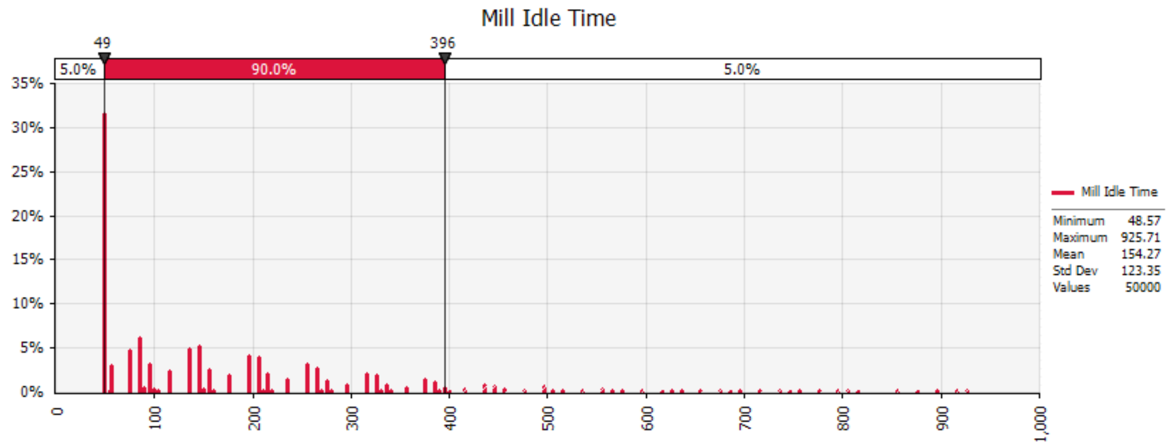
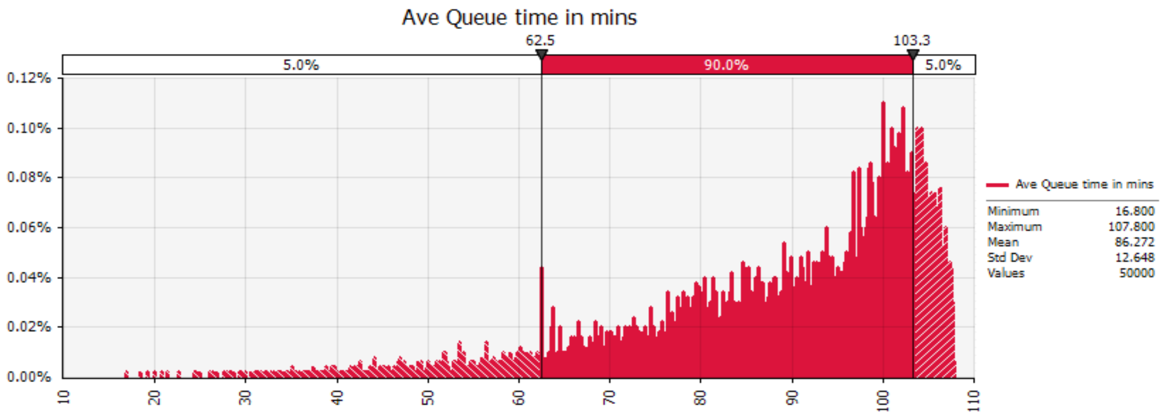


Figure 3: Distribution of Average queue time (in minutes)



The results show that both the mill idle times and the queue times vary according to the number of trucks arriving from each location. The mill idle time can vary from 925 minutes to 48 minutes while the average queue time per truck can vary from 107 to 17 minutes.

A selection of results according to various quotas from each location is presented below:

Table 2: Selection of result from Monte Carlo simulation

Location	L_1	L_2	L_3	L_4	L_5	Total mill idle time (mins)	Average queue time (mins)
Distance (km)	30	60	100	150	200		
Time taken (hrs) to travel to mill*	0.5	1	1.67	2.5	3.33		
Combination of quota 1 (# of trucks)	22	10	24	22	22	48.57	62.4
Combination of quota 2(# of trucks)	21	27	21	12	19	175.71	82.54
Combination of quota 3(# of trucks)	18	15	14	37	16	865.71	64.64

As shown in table 2, combination 1 is the best choice of quotas from each location because of least mill idle time and minimal average queue time. Combination 2 on the other hand has increased mill idle time and increased average queue time. Combination 3 has the worst mill idle time but relatively lesser average queue time when compared to combination 2. Since mill idle time is costlier than queue time, combination 1 is the best choice and combination 3 the worst.

4.2. Scenario 2

Let's again consider an approach with 5 locations (n = 5) with the following quantities. Note that this time the cane quantity at each location varies. For instance, location

L_1 has 100 tonnes of cane, i.e. equivalent to a load of 10 lorries whereas L_5 has 500 tonnes of cane available.

The results of a simulation with 50000 iterations are as below:

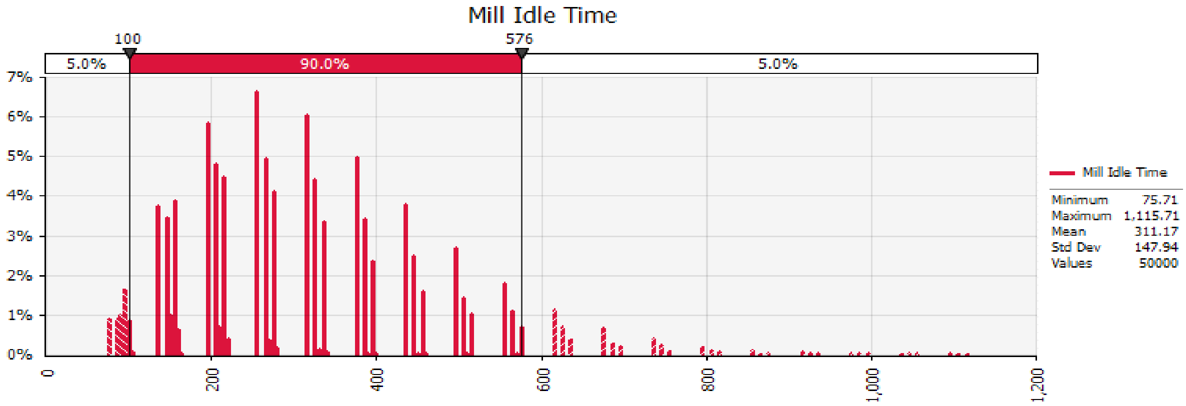


Figure 4: Distribution of Mill idle time

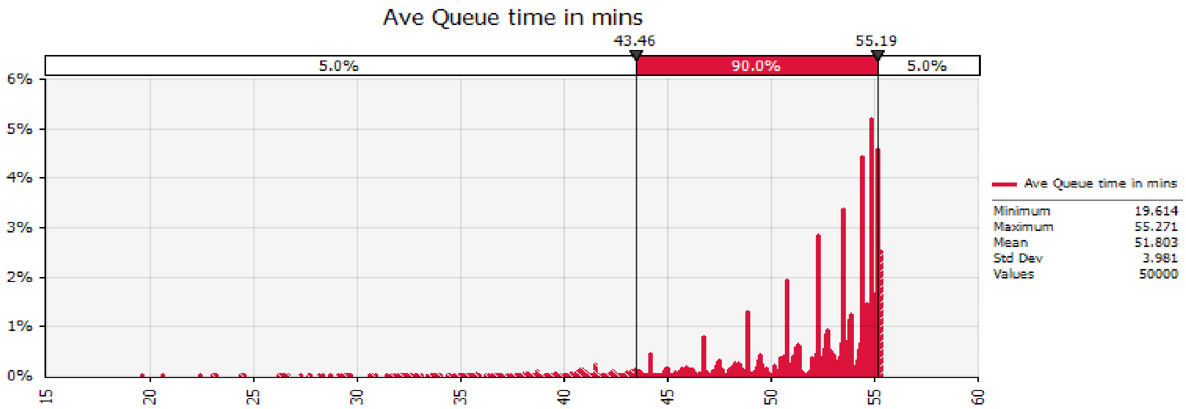


Figure 5: Distribution of Average queue time (in minutes)

The results again show that both the mill idle times and the queue times vary according to the number of trucks arriving from each location. The mill idle time can vary from 1115 minutes to 75 minutes while the average queue time per truck can vary from 55 to 19 minutes.

A selection of results according to various quotas from each location is presented below:

Location	L_1	L_2	L_3	L_4	L_5
Distance (km)	30	60	100	150	200

Cane Quantity (tonnes)	100	200	500	500	500
Time taken (hrs) to travel to mill*	0.5	1	1.67	2.5	3.33

Table 3: Input variables to Monte Carlo simulation

A selection of results according to various quotas from each location is presented below:

Location	L_1	L_2	L_3	L_4	L_5	Total mill idle time (mins)	Average queue time (mins)
Distance (km)	30	60	100	150	200		
Time taken (hrs) to travel to mill*	0.5	1	1.67	2.5	3.33		
Combination of quota 1 (# of trucks)	10	20	24	23	23	75.7	55.3
Combination of quota 2(# of trucks)	10	13	28	27	22	280	38.3
Combination of quota 3(# of trucks)	10	20	40	7	23	995.7	23.2

Table 4: Selection of result from Monte Carlo simulation

As shown in table 4, combination 1 is the best choice for quotas from each location because of least mill idle time and a low average queue time. Combination 2 on the other hand has increased mill idle time and comparatively lower average queue time. Combination 3 has the worst mill idle time but lowest average queue time when compared to combination. Again since mill idle time is costlier than queue time, combination 1 is the best choice and combination 3 the worst.

As pointed out earlier, mill operators would prefer to minimise mill idle time as opposed to queue time due to the cost factor. Nonetheless, using the Monte Carlo method provides one with the opportunity to choose the quota they believe is workable and know the effect of making that choice. Due to the nature of the Monte Carlo process, many combinations of various possible quotas are available to view together with their respective mill idle time and queue time. This feature can prove to be very handy to make contingency plans for events such as initially advised quota not achievable due to unforeseen events such as breakdowns and adverse weather conditions. Thus if the operator has to make immediate decisions as to what is the second best option, the results of Monte Carlo can be readily used. For instance, if the Monte Carlo optimised quota is not workable, then the second best quota or other quotas can be chosen as an alternative from the simulated results together with the knowledge of respective expected mill idle time and queue time.

5. CONCLUSION

Using two varying scenarios an optimal cane delivery scheduling using the Monte Carlo Method was shown. The demonstrated model focused on minimizing mill idle time as a first criterion and lorry queue time as the next, while incorporating different travel times to the mills from various locations, processing time of mills and time taken to cut cane and load lorries at the farms. The generated output not only provides the optimal schedule or quota from each farm but also provides numerous other quotas with its respective mill idle time and average queue times.

This feature of having multiple results, together with the optimal solution, provides versatility in that the other results could be used for planning and contingency purposes in the event that the optimal solution is not usable. For instance, if a decision has to made at the eleventh hour to revise the delivery schedule, one does not have to run the simulation again but instead use the generated scenarios to choose the one that best suits the situation and also have the knowledge of the consequence of choosing the particular scenario i.e. knowledge of mill idle time and queue time. The can also equip the operator of the mill to adjust the crushing rate of the mill appropriately so as to minimise any financial loss due to mill idle time.

Furthermore, Monte Carlo techniques are nowadays widely used for many applications including all types of optimization algorithms due to its easy to understand, use and implement unlike traditional heuristics or optimisation algorithms. This technique can be used in place of traditional heuristics methods either because heuristics methods fail or it is too difficult to implement. Monte Carlo technique can also incorporate the possibility of correlation within variables and also derive a more accurate scenario analysis by using probabilistic distributions of all the variables including the speed of the trucks/lorries and the distances of the farms from the mills. Our future research will incorporate the scenario whereby actual data is obtained from mills and optimised to see if the scheduling could have been done better.

BIBLIOGRAPHY

Abel, D. J., et al. (1981), "A Routing And Scheduling Problem For A Rail System: A Case Study.". Journal of the Operational vol. 32, pp767-774.

Fiji Sugar Corporation Ltd and Subsidiary Companies (2014), Fiji Sugar Corporation Annual Report. 2014. Web. 31 May 2016.

Hansen, A.C., Barnes, A. and Lyne, P.W.L. (2001)., Using computer simulation to evaluate sugarcane harvest-to-mill delivery systems. Proceedings of the Seventh International Conference on Computers in Agriculture, pp 98–107.

Higgins, Andrew. (2006) "Scheduling Of Road Vehicles In Sugarcane Transport:". European Journal of Operational Research, vol. 170, pp 987-1000.

Kochanski, G., 2005. Monte Carlo simulation. Viewed on 31 May 2016, http://kochanski.org/gpk/teaching/0401Oxford/MonteCarlo.pdf

Milan, E.L., Fernandez, S.M., Pla, L.M., 2003. The transportation problem of sugarcane, Working paper at the Mathematics, Department of the University of Lleida, Spain.

Pinkney, A.J. and Everitt, P.G. (1997). Towards and integrated cane transport scheduling system, Proc. Aust. Soc. Sugar Cane Technol., vol 19, pp 420–425.

Vose, D, (2008), Risk Analysis: A Quantitative Guide, Wiley, 2008.