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An integrated approach to optimise sugarcane rail operations

Abstract:

In Australia, the railway system plays a vital role in transporting the sugarcane crop from farms to mills. The sugarcane transport system is complex as it routines a daily schedule, which consists of a set of train runs to satisfy the requirements of the mills and harvesters. A constrain programming approach is used to formulate this complicated system. Metaheuristic techniques and constraint programming are hybridised as an efficient solution approach. Thus, a better sugarcane transport scheduling system is achieved to maximise the throughput of sugarcane transport. A numerical investigation is presented and demonstrates that high-quality solutions are obtainable for industry-scale applications in a reasonable time.

Keywords: Sugarcane Transport; Train Scheduling; Job Shop Scheduling; Constraint Programming; Metaheuristics

1. Introduction

1.1.1 Background

Australia is the world's third largest exporter of raw sugar after Brazil and Thailand, with around $2.0 billion in export earnings. Approximately 85% of the raw sugar produced in Queensland is exported. Approximately 4400 cane farming entities are growing sugar cane on a total of 380,000 hectares annually, supplying 24 mills, owned by 8 separate milling companies. Up to 35 million tonnes of sugarcane produce up to 4.5 million tonnes of raw sugar, 1 million tonnes of molasses and 10 million tonnes of bagasse annually. The sugar industry directly employs about 16,000 people across the growing, harvesting, milling and transport sectors (Australian Sugar Milling Council 2014).

Transport systems play a vital role in the raw sugar production process by transporting the sugarcane crop between farms and mills. The sugarcane transport system uses a daily schedule of runs to meet the needs of both the harvesters and the mill. The sugarcane transport system is an important element in the raw sugar production system, accounting for over 35% of the total cost of raw sugar production in Australia (Australian Sugar Milling Council 2014).

The sugarcane transport system is a complex system that includes a large number of variables and elements. These elements work together to achieve the main objectives of satisfying both mill and harvester requirements and improving the efficiency of the system in terms of low overall costs. The fast growing demand of Australian sugar was affected by the inefficiency of the sugarcane rail system, in which the railing bottlenecks increase the interruption time of cane crushing at Mill and reduce the cane quality after harvesting. The transport sector has a critical impact on the overall cost of a sugarcane rail system. Millions of dollars was costed by sugar companies and risking the future of exports because of these bottlenecks. Some potential negative effects of cane transport on the whole system include delaying the arrival of sugarcane to the mill; delaying the arrival of empty sugarcane bins to harvesters at farms; causing the harvesters to wait for empty bins and increasing their costs; and increasing extra costs through the need for the larger numbers of locomotives and sugarcane bins.

These costs include delay, congestion, operating and maintenance costs. Integration of the harvesting, transport and milling elements in the value chain of the Australian sugar industry can increase the performance efficiency of the system. For example, optimising the delivery and collection times throughout the rail system requires the information about harvesting times, harvesting rate, harvesters' locations, the crushing rates at mills and etc.

Producing efficient schedules for the cane rail transport system can reduce the cost and limit the negative effects that this system can have on the raw sugar production system. Many publications have discussed and solved problems in this sector to improve the efficiency of the system's performance. The scheduling of locomotive movements on cane railways has proven to be a very complex task (Masoud et al., 2015). Various optimisation methods have been used over the years to try to produce an optimised schedule that eliminates or minimises bin supply delays to harvesters and the factory, while minimising the number of locomotives, locomotive shifts and cane bins, and the cane age.

1.2 Problem Description

Sugarcane is transported in specially designed bins called sugarcane bins. The railway system can generally operate for 24 hours a day, while the harvesting period is limited to about 12 hours each day. A sugarcane railway network uses a single track and has many interconnecting lines (segments) and sidings (delivering and collecting points). Each line has different sections and each section can be defined between track features such as sidings or passing loops. The sugarcane railway system performs the following two main tasks: delivery of empty bins from the mill to sidings and collections of full sugarcane bins to the mill. From the perspective of the whole transport system, the mill serves the function of converting full bins into empty bins, while the harvesters convert empty bins to full bins.

Each harvester operating at a siding has a daily allotment of bins, which often exceeds the capacity of one siding. Sidings have a finite capacity that should not be exceeded in practice. In this case, several empty bin deliveries are typically required each day to maintain an empty bin supply to the harvesters. Each train can haul a limited number of empty bins and full bins, depending on the capacity of the train. For safety reasons, the train does not generally haul mixed trains of empty bins and full bins. Thus, empty bin deliveries must take place before full bin collections during each train run.

The sugarcane transport system uses a daily schedule, consisting of a set of train runs, to satisfy the requirements of the mill and harvesters. The sugarcane transport system plays a significant role on the performance of the sugar production process. Potential negative effects of a poor transport system include: stopping the supply of cane to mill, causing interruptions to the raw sugar production process; delaying the arrival of sugarcane to the mill; allowing cane to deteriorate and lose sugar quality; delaying the arrival of empty cane bins to harvesters causing the harvesters to waste time and money waiting for empty bins; increasing cane production costs through inefficiencies in the sugarcane transport system itself, and in the harvesting and raw sugar production processes. Sugarcane transport systems are very complicated systems and these systems face many challenges which affect the overall cost or the performance of sugarcane system. The challenges include:

- Scheduling passing of trains on the single rail track to improve performance of the railway system.
- Maintaining a non-interrupted supply of full bins to the mill and empty bins to the harvesters.
- Limited harvesting hours. In Australia, most harvesting operations occur during daylight hours while the transport system and mill operate continuously. As a result, the cane bins are used for temporary storage of the harvested crop at sidings and at the mill. Long storage times reduce sugarcane quality and crop profitability.
- Minimising the number of locomotive runs to reduce operating costs.
- Reducing the time between harvesting and crushing (cane age) to keep sugarcane quality high.

Due to these real-life challenges, there is an urgent need for an efficient sugarcane transport schedule that will be produced by rail scheduler. A real-time schedule optimiser should be developed to maximise the throughput of the overall sugar production system.

In this paper, single track railway systems use blocking constraints to achieve safe operations. Blocking constraints work by preventing more than one train from occupying a track section at the same time and help in resolving conflicts throughout the railway network (Liu and Kozan, 2009, 2011a-b). Blocking constraints have been applied to different types of railway networks such as mining or freight railways (Kozan and Liu, 2012 and 2015). A segment blocking approach was also considered in the model of Masoud et al. (2011 and 2015) in which a new model was presented to solve the sugarcane rail transport system problem. In comparison, sugarcane railway networks include many segments (branches or lines), as shown in Figure 1. Some of these branches do not have passing loops. Thus, complete branches are sometimes used as substitute passing loops.

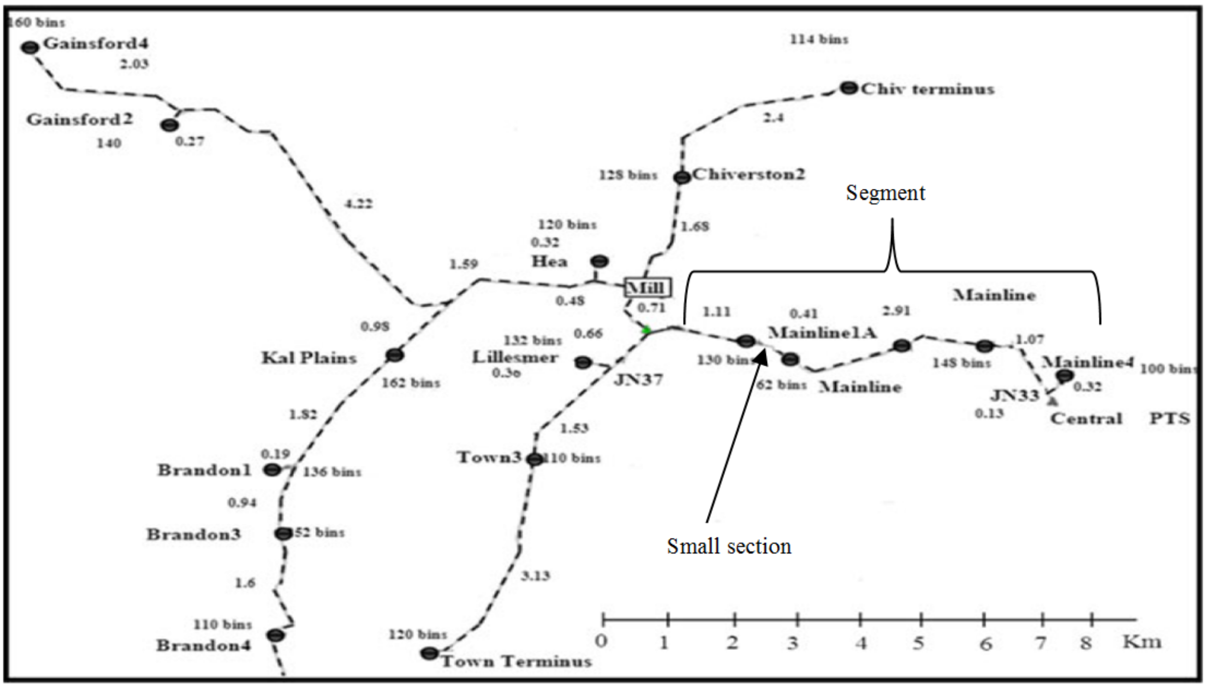

Figure 1: A real sugarcane rail network

In this paper, a new CP model is developed under limited capacity constraints of trains and rail sidings. The successive short sections may be combined to form one section. This ensures that the length of the train is less than the length of the section and so section blocking constraints can be applied. The sidings located in consecutive short sections maybe combined with their nearest siding to work as one siding, as shown in Figure 1. The capacity and allotment of the resulted siding equals the capacities of the original sidings and the total allotments of these sidings. As a result, the system efficiency improves by decreasing the total waiting time which affect positively the total operating time of trains.

In this paper, an integrated hybrid approach is developed to solve large-scale sugarcane rail scheduling instances in a more efficient way. This approach depends on integrating CP and the two metaheuristic techniques (i.e., simulated annealing and tabu search) to produce high quality solutions in a reasonable CPU time.

1.3 Literature Review

Solutions techniques for the sugarcane rail scheduling problems are rare in the literature. Everitt and Pinkney (1999) described an integrated set of tools to manage the performance of a sugarcane transport scheduling system. This work was designed to achieve integration between the schedule simulation programme, the schedule generating programme and Traffic Officer Tools. Higgins and Davies (2005) introduced a simulation model for the capacity of sugarcane transport systems in Australia. This capacity was determined by estimating variables such as the number of trains used in the system and their movements, the number of bins and the time spent waiting for the empty bins at farms.

In comparison to Mixed Integer Programming (MIP), Constraint programming (CP) approaches have been widely used to solve complicated scheduling problems. CP has the ability to model many different types of combinatorial optimisation problems especially rail transport system problems (Rodriguez, 2007). CP techniques have the ability to solve feasibility problems and can deal with conflicting objectives (Cortés et al., 2014 and Goel et al., 2015). CP that deals with problems defined within a finite set of possible values for each variable is the main technology used for solving mathematical formulation problems (Russell and Urban 2006; Schaerf 1999; Henz et al., 2004; Hoeve and Katriel, 2006).

Moreover, CP has been applied to solve many types of real-world scheduling problems. Martin et al. (2001) proposed a new approach using Constraints Logic Programming to solve sugarcane railway scheduling problems using a Prolog language with extra features suitable for the system. This technique produced daily schedules to minimize the number of locomotives and their runs, and satisfy constraints of the system such as siding capacity and locomotive hauling capacity. Issai and Singh (2001) developed train scheduling algorithms based on an object oriented constraint based heuristic and two hybrid algorithms which integrate the heuristic techniques with tabu search and simulated annealing strategies. Masoud, Kozan, and Kent (2010) developed a new CP model for the sugarcane rail transport system problem and solved small-size instances by ILOG-CPLEX. As yet these techniques cannot obtain accurate solutions for large-scale instances in a reasonable time.

The main contribution of this paper is to develop a new CP model for the sugarcane rail transport system and conduct a comparative study of different solution approaches based on the hybridisation of CP and metaheuristics to solve the sugarcane railway scheduling problem. The classical mathematical programming approach such as mixed integer programming (MIP) is also compared with CP and the proposed integrated approach in this study. While memory and solution time may rise exponentially as more integer variables are added and therefore MIP may be inapplicable to solve large-size instances. In comparison, CP defines "higher-level" all-different constraints in a better way (i.e., less memory and solution time).

The remainder of the paper is outlined as follows. In Section 2, a CP model is presented to formulate the problem and describe the main mechanism of the sugarcane transport system. Several integrated approaches are presented in Section 3 to solve the problem. Extensive computational results are reported in Section 4 and the conclusions are summarised in the final section.

2. CP MODELLING

The sugarcane rail scheduling problem as discussed in the previous section is formulated in this section using the proposed constraint programming (CP) model in Section 2.1. The CP model provides the main constraints of the sugarcane rail system and explains the main mechanism of delivering and collecting bins at each siding including the directions (outbound or inbound) and times of the delivering and collecting operations.

2.1 CP Model

A sample sugarcane rail system is modelled as in Figure 2, in which eight sections are single with one unit ($s_{1,1}$, $s_{3,1}$,$s_{6,1}$,$s_{8,1}$,$s_{9,1}$,$s_{11,1}$,$s_{13,1}$ and $s_{15,1}$), five sections are double with two parallel units (($s_{5,1}$ and $s_{5,1}$), ($s_{7,1}$ and $s_{7,2}$), ($s_{10,1}$ and $s_{10,2}$), ($s_{12,1}$ and $s_{12,2}$), ($s_{16,1}$ and $s_{16,2}$)) and two sections are triple with three parallel units (($s_{2,1}$ and $s_{2,2}$ and $s_{3,1}$), ($s_{14,1}$ and $s_{14,2}$ and $s_{14,3}$)). There are six trains for seven harvesters at seven siding points ($s_{2,3}$, $s_{5,2}$, $s_{7,2}$, $s_{10,2}$, $s_{12,2}$, $s_{14,3}$ and $s_{16,2}$) in the system.

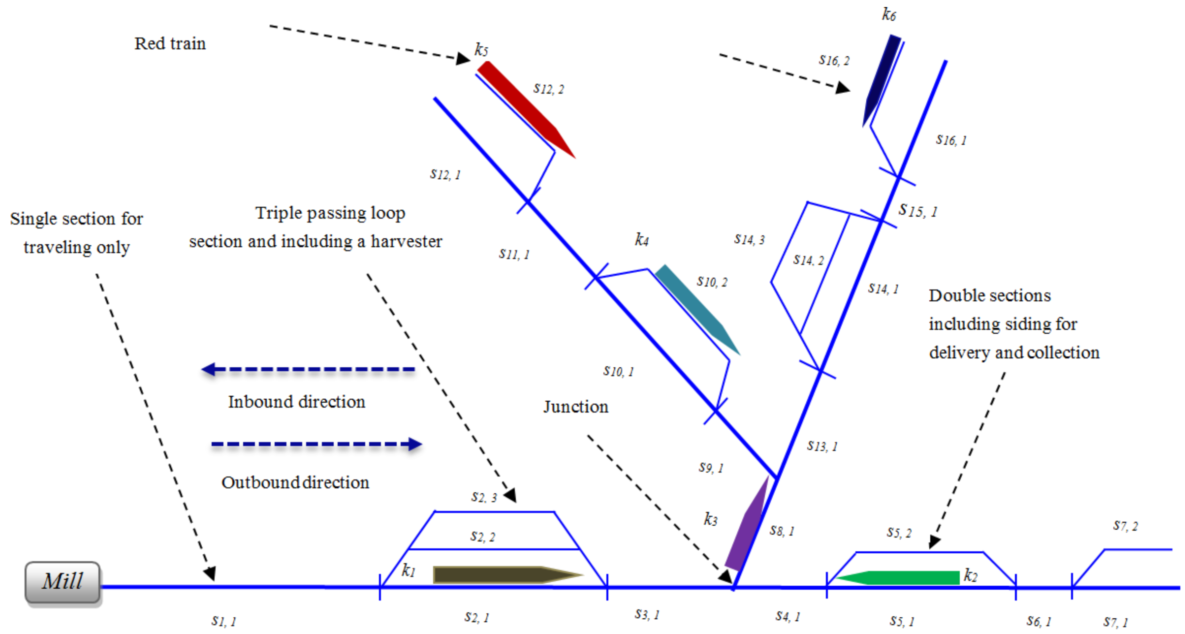

Figure2: A simple sugarcane rail network.

Modelling any problem using CP is restricted by the CP package used because of the differences in constructs available in various modelling languages. In this paper, ILOG's Optimization Programming Language (OPL) was used to solve the CP model. CP model uses fewer constraints than MIP because CP can combine several constraints to work as one constraint using the statement OR "$\vee$" such as in passing priority constraints and runs order constraints. CP uses variable subscripts instead of binary decision variables. For this reason, there are no binary decision variables in CP, while the corresponding MIP model (Masoud *et al.*, 2011) includes many of them such as q_{krosu} and X_{krsu} as shown below.

$$X_{krsu} = \begin{cases} 1, \ if \ \ train \ k \ assigned \ to \ section \ s \ on \ unit \ u \ during \ run \ r. \\ 0, \ otherwise. \end{cases}$$

$$q_{krosu} = \begin{cases} 1, \ if \ \ the \ operation \ o \ of \ \ train \ k \ requires \ section \ s \ on \ unit \ u \ during \ run \ r. \\ 0, \ otherwise. \end{cases}$$

In OPL, there has a set of constructs for scheduling problems to develop an effective CP model. *Unary resources* represent the resources (machines) that can process only one operation at the same time. The rail sections and the parallel units at each section are modelled as *unary resources*. Each train run is a *unary resource* because a train can only conduct one run at a time and each operation requires a *unary resource* to be processed on it. Each operation is associated with a start time and duration. This function returns a value of true if an operation o of train k is processed on the unary resource, unit u on section s, and run r is processed by train k.

In this section, a sugarcane transport system model using CP in the OPL language environment is described.

Parameters

K	number of available trains
k, k'	index of a train, $k, k' = 1,2, \dots, K$
S	number of rail sections
s	index of a section, $s = 1,2, . . , S$
U_s	number of units on sections s
u	index of a unit of each section; $u = 1,2, \dots U_s$, where u is a unary resource
O_r	number of operations in run r
o	index of operations in a run; $o = 1,2 \dots O_r$
e_k	capacity of train k on empty bins
f_k	capacity of train k on full bins
A_{us}	allotment of the unit u of the section s, measured in number of bins
y_{us}	siding capacity of the unit u of the section s
g_{kus}	running time of train k on unit u of section s
H_s	harvester start time at siding s
γ_s	harvesting rate of harvester at siding s

Variables

R_k	number of runs for train k
r, r'	index of run r or r' for a train, $r, r' = 1,2, \dots, R_k$
B_{krous}	number of full bins collected from unit u at section s by train k during operation o and run r
α_{krous}	number of empty bins delivered for unit u at section s by train k during operation o and run r
t_{krous}	start time of operation o of train k in run r on unit u at section s
l_{krous}	completion time of operation o of train k in run r on unit u at section s
C_{max}	makespan

The objective is to minimise the makespan, equivalent to maximise the throughput.

$$\textit{Minimise} \quad \max\{l_{krous}\} \quad \forall\, k, r, o, u, s \tag{1}$$

Subject to:

$$l_{krous} \geq t_{krous} + g_{kus} \quad \forall\, k, r, o, u, s \tag{2}$$

$$(t_{krous} + g_{kus}) \leq t_{kr(o+1)us} \vee t_{r(o+1)us} \leq (t_{krous} + g_{kus}) \quad \forall\, k, r, o, u, s \tag{3}$$

Constraint (2) defines the condition on an operation's start time and completion time, while Constraint (3) satisfies the sequencing relationship of two consecutive operations in a run.

$$t_{krous} \geq (t_{k'r'o'us} + g_{k'o'us}) \vee t_{k'r'o'us} \geq (t_{krous} + g_{kus}) \tag{4}$$

$\forall\, k, k', r, r', o, o', u, s;\ k \neq k'\, and\ r \neq r'$

Constraint (4) satisfies the passing constraints of two trains in a rail track.

$$(t_{kr0us} + g_{kus}) \leq t_{kr'o'us'} \vee (t_{kr'Ous'} + g_{kus'}) \leq t_{krous} \quad \forall\, k, r, o, u, s, s' \tag{5}$$

Constraint (5) satisfies the sequencing relationship of two consecutive runs for each train.

$$\sum_{o=1}^{O_r} \sum_{s=1}^{S} \sum_{u=1}^{U_s} \alpha_{krous} \leq e_k \quad \forall k, r \tag{6}$$

$$\sum_{o=1}^{O_r} \sum_{s=1}^{S} \sum_{u=1}^{U_s} B_{krous} \leq f_k \quad \forall k, r \tag{7}$$

Constraints (6)-(7) satisfies the train capacity with empty bins and full bins.

$$\text{o}'\text{precedes o} \Rightarrow (\alpha_{krous} \leq e_k) \wedge (B_{kro'us} = 0) \quad \forall\, k, r, o, o', u, s \tag{8}$$

$$(\text{o proceeds } o' \Rightarrow B_{kro'us} \leq f_k) \wedge (\alpha_{kro'us} = 0) \quad \forall\, k, r, o, o', u, s \tag{9}$$

Constraints (8)-(9) ensure the empty bin delivery is in the oubound direction and the full bins collecting is in inbound direction.

$$\sum_{k=1}^{K}\sum_{r=1}^{R_k}\sum_{o=1}^{O_r} \alpha_{krous} = A_{us} \quad \forall u, s \tag{10}$$

$$\sum_{k=1}^{K}\sum_{r=1}^{R_k}\sum_{o=1}^{O_r} B_{krous} = A_{us} \quad \forall u, s \tag{11}$$

Constraints (10)-(11) are bin constraints that ensure the deliveerd or collected bins to each harvester at each rail siding must equal the daily harvester's allotemnet.

$$\alpha_{krous} + B_{krous} \leq y_{us} \quad \forall u, s \tag{12}$$

Constraint (12) satisfies the siding capacity as each siding has a limited capacity for crossing or overtaking.

$$t_{k1ous} \leq H_s + \frac{\propto_{kRous}}{\gamma_s} \tag{13}$$

$$t_{krous} \leq t_{k(r-1)ous} + \frac{\propto_{k(r-1)ous}}{\gamma_s}; r > 1 \tag{14}$$

Constraints (13) and (14) are developed to optimise the time of delivering empty bins without delays.

$$B_{k1ous} \leq (t_{k1ous} - H_s) * \gamma_s \tag{15}$$

$$B_{krous} \leq \left(t_{krous} - t_{k(r-1)ous}\right) * \gamma_s \; ; r > 1 \tag{16}$$

Constraints (15) and (16) optimise the number of full bins collected to be no more than the produced number of full bins at each siding at each run.

The sugarcane train scheduling needs to satisfy the harvesters' requirement for a continuous supply of empty bins to harvest continuously and the mill requirement for a continuous supply of full bins to crush continuously under limited number of bins and limited sidings capacity in a specific makespan (optimised makespan to finish all rail operations daily). Optimising the delivery and collection times can satisfy the empty and full bin requirements for each rail section and mill in the sugarcane rail system, and reduce the time between harvesting and crushing (sugarcane age) to keep sugarcane quality high.

The sugarcane rail model above is developed to describe the main mechanism of the the delivering and collecting operations at each siding and to avoid any delays in the sugarcane rail system which causes interruptions for the system work. The proposed model above includes the main steps which are followed to deliver and collect bins during each run for each train. The model fundamental assumed that there are two operations o, o' that will be implemented on each section during the train run r. The first operation will be executed in the outbound direction and the second operation will be executed in the inbound direction. In addition, model considers no delivering or collecting if the section is a passing section used only to allow trains to pass and not as a siding for delivering or collecting bins. The first operation is assigned for delivering bins only in the outbound direction. No collecting occurs in the outbound direction for efficient and safe operation and saving the fuel costs. The second operation on the same section and the same train will be assigned for collecting full bins in the inbound direction.

Delivery and collection times of empty and full bins at each siding are involved in the proposed model to remove any delays throughout the transport system, where the proposed model supposed that the delivered empty bins during the last run to a siding during a day are provided for use the next day when the harvester commences. The number of bins to be delivered is determined by considering the total allotment for each siding and the siding capacity. The visits to each siding for one day are organised in the next procedure. In the proposed model, the main aim of the first run to a siding for the day is to deliver empty bins which are to be used until the train's next run. The number of delivered empty bins in the first run of the day should be sufficient to satisfy the harvester's needs without interruption until the second run to the siding. Second and subsequent visits up to the last run are constructed to deliver the empty bins to the siding that will be used until the next run. The last run is required to deliver the empty bins to the siding to be used the next day until the first run and to collect the last of the full bins filled today. The siding capacity and the anticipated number of full bins at the siding are taken into account during the delivery of empty bins at the siding. The allotment of the delivered empty bins equals the allotment of the collected full bins each day. The number of full bins collected depends on the harvesting rate at each siding and the visit times.

3. Solution Approaches

In this section, different solution approaches are developed for solving the large-scale sugarcane rail scheduling instances. The solution representation of the sugarcane rail scheduling problem is a new a scheduler as presented in Figure 3 where the vertical axis is the section number and the horisental axis is the time in hour. There are three trains; red, green and blue are used in the system to visit the section and return to the mill. For illustration, some waiting times of trains passing and the conflicts are shown in the Figure 3.

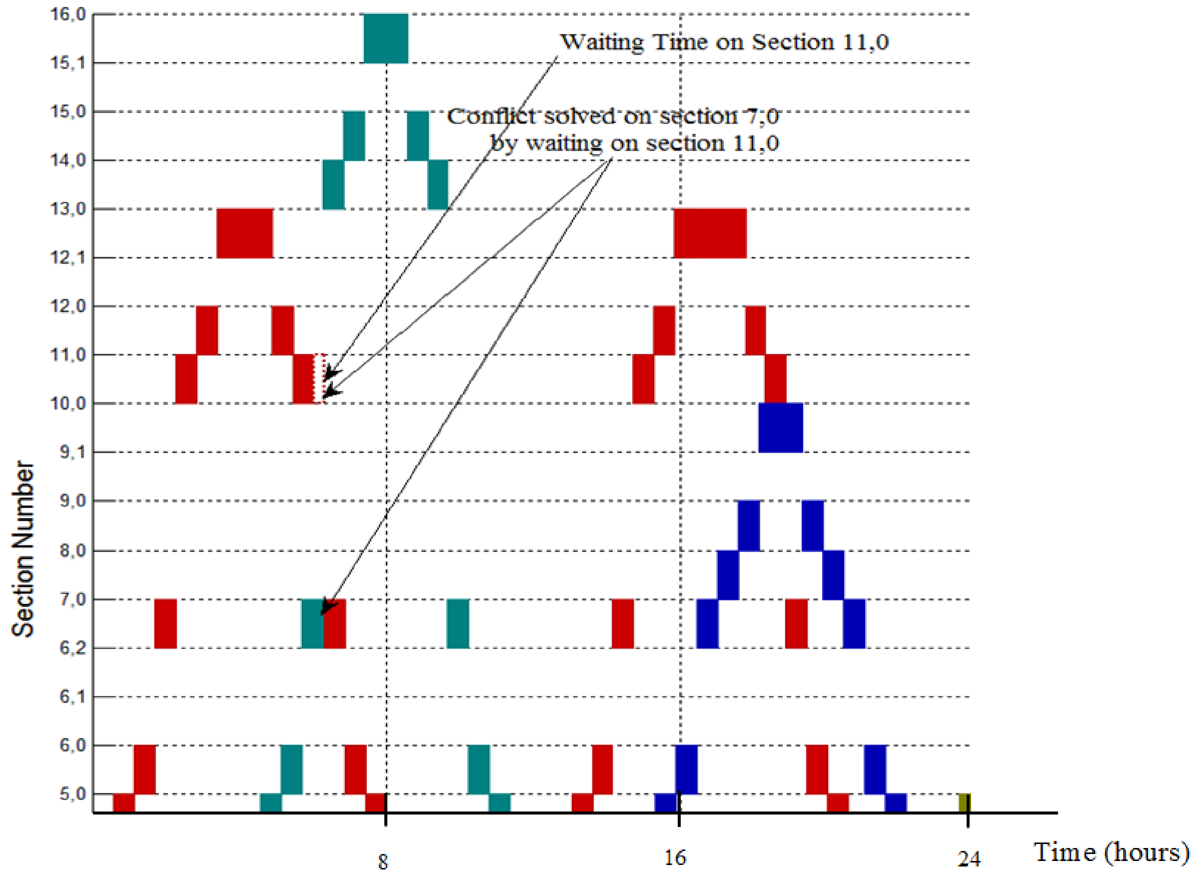

Figure 3: The solution representation of the sugarcane rail scheduling problem

3.1 A CP-DFS Approach

The proposed CP approach depends on two main features: global constraint and search techniques, both of which are integrated in the CP solution procedure. The global constraint function is applied to globally capture the relation between arbitrary number of variables through different constraints by removing infeasible solutions using filtering and search methods. CP defines the different constraints in the proposed model using a global constraint function such as *Alldiff*$(C_1, C_2, \ldots C_n)$ function in a better way, resulting in less memory usage and computational time. Depth-First Search technique (DFS) technique is used as a search technique. DFS starts at the root node and proceeds by descending to its first descendant.

This process continuous until a leaf is reached. Then, the process backtracks to the parent of the leaf (node without children) and descends to its next descendant until the solution is discovered (Tsin, 2002; Her and Ramakrishna, 2007). The detail of the proposed adapted DFS technique for optimising the sugarcane railing operations is presented below.

Begin

Step 1 *Initialize set of trains, trains capacity, track sections, siding capacities, siding allotment, harvesters start time and harvesters rate*

Step 2 *While ((delivers to siding s ≤ allotment of s) OR (collections to siding s ≤ allotment of s))*

Step 3 *Let schedule = { }*

Step 4 *Select operation of unscheduled operations of train's run*

Step 5 *Assign a possible time for the start of the operations considering the precedence*

Step 6 *Construct rail constraints; siding constraints; trains constraints*

Step 7 *Call constraint propagation using global constraint function, lldiff*($C_1, C_2, \ldots C_n$).

Step 8 *If there is no conflict then*

8.1 *Remove the operation from unscheduled operations*

8.2 *Push operation onto schedule*

Step 9 *Else*

9.1 *Call a backtracking procedure to the most recent scheduled operation and test a new value of its domain.*

Step 10 *End if*

Step 11 *End While*

End

3.2 A hybrid CP-TS/SA approach

A hybrid approach is based on the integration of the global constraint technology in CP and different metaheuristic techniques such as simulated annealing and tabu search, as illustrated in Figure 4. The above hybrid (CP-TS/SA) algorithm starts with constructing an initial solution using the CP approach where all constraints and time window of the train operations are identified and checked using constraint propagation. A backtracking procedure is used for removing any conflicts through the rail systems by testing the most recent scheduled operation and test a new value of its domain. The second main step in the hybrid (CP-TS/SA) is to develop the first iteration solution of TS by constructing a new neighbourhood of the CP schedule. Evaluate the first initial solution of TS by comparing with the CP solution to obtain best solution. The obtained solution in second step will integrate with the first iteration of SA in the third main step in the hybrid (CP-TS/SA) to produce a new solution by generating a new neighbourhood. The solution of the third step will be used again as initial solution in the second step to start second iteration of TS. The stop criteria in this algorithm are no improvements in the makespan value for small change of temperature T.

In the SA, generic parameters are identified such as temperature T that is updating through the iterations using the stochastic element α; $0<\alpha<1$, where $T_{new}= \alpha T$. The element *ε is a* small number that can be used to evaluate the new solution. The stochastic element α value in SA and the maximum number of iterations in TS have a significant effect on the final results of any solution technique. Typical values for cool parameter α in simulated annealing vary between 0.8 and 0.99 (Aarts et al., 2005). Generic parameters are tested to be used for the sugarcane rail transport scheduling problem. The hybrid techniques depend on the cool parameter α = 0.90, initial temperature T_0= 100 and maximum number of iterations 250 iterations.

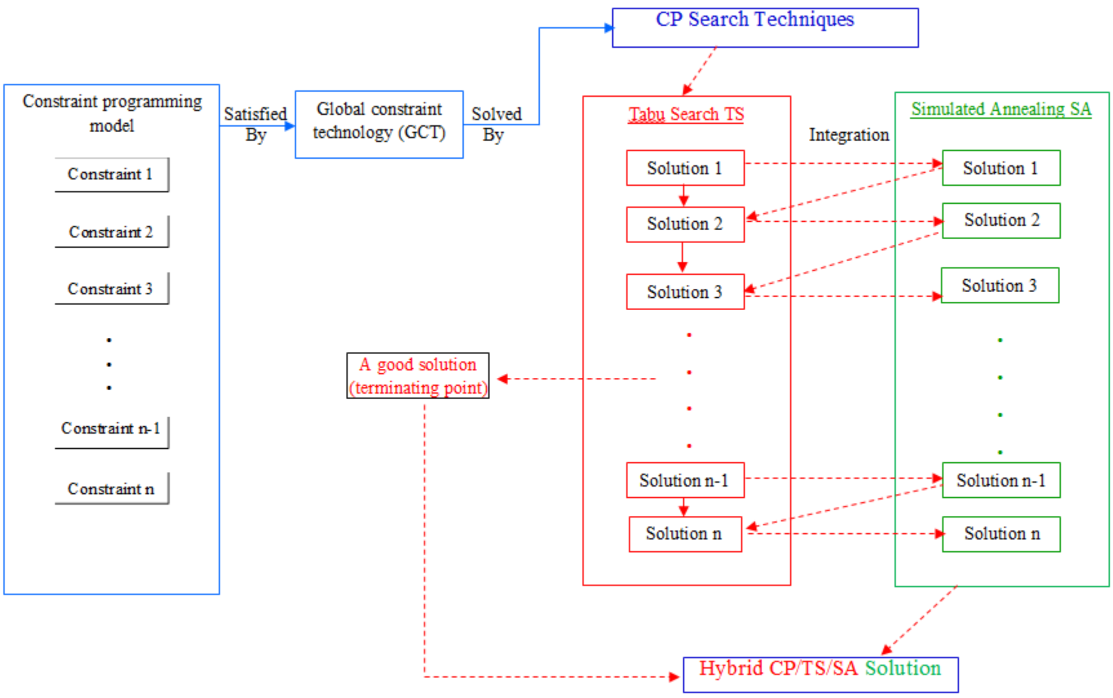

Figure 4: The framework of a hybrid CP-TS/SA algorithm

The main steps of the hybrid CP-TS/SA algorithm are detailed below:

Step 1 Initialise the following parameters

1.1 Set the large value for the temperature $T=T_0$

1.2 Set the value of the cooling parameter α $0<\alpha<1$

1.3 Set the initial tabu list

1.4 Set the maximum number of iterations, max_iter

1.6 Set an initial feasible solution by using CP technique

1.7 Set current solution = initial feasible solution

Step 2 Apply tabu search technique

2.1 While iter <=max_iter,

Generate a neighbourhood of a current solution

Let (k,k') are the adjacent two trains require same section s by operations o and o' respectively

Swapping (k,k', o, o', s) → (k',k, o', o, s)

Check the feasibility time window, trains and sidings capacity

Obtain a Tabu Search solution

Evaluate the Tabu Search solution = $makespan^{TS}$

Calculate $\Delta=makespan^{TS}$ *– current makespan*

2.2 If $\Delta<0$ *then Set current solution= Tabu Search solution.*

2.3 Else, apply simulated annealing technique

While (T is in cooling range)

Generate a neighbourhood of a current solution

Let (k,k') are the adjacent two trains require same section s by operations o and o' respectively

Swapping (k, k', o, o', s) → (k', k, o', o, s).

Check the feasibility time window, trains and sidings capacity.

Obtain a new solution.

Evaluate the new solution= $makespan^{hybrid\ (CP/TS/SA)}$

Calculate $\Delta= makespan^{hybrid(CP/TS/SA)} - makespan^{TS}$

If $\Delta<0$*, then set the current solution by the new solution; else If* $Pr(accepted)=EXP(\Delta/T)>\varepsilon$*, then also update the current solution*

Else, set current solution=Tabu Search solution

Update T according to $T=\alpha T$

2.4 Update tabu list

4. Computational Results

The hybrid techniques depend on the cool parameter α = 0.90 and 250 iterations. In Table 1, the yellow color highlights the best CPU time of the metaheuristic techniques, while the green color represents the best solution quality (lowest makespan). Each result shown in Table 1 is the average makespan from 67 tests. Table 1 shows that the number of variables and constraints in CP model are less than the MIP model in all cases. The initial solution using CP is presented in the eighth column in Table 1 based on makespan criterion. The value and CPU time of makespan are shown in Table 1 for different hybrid techniques; CP/TS, CP/SA, TS/SA and CP-TS/SA comparing with the CPLEX software solution of mixed integer programming as an optimal solution. Hybrid (TS/SA) is the hybrid technique that had been developed by Masoud et al. (2015) to solve the sugarcane rail scheduling problem using the same practical cases.

The results in Table 1 pointed out that most of the 3 and 4 train instances, the CPU time was also substantially less. The mixed integer programming method, however, works well only with small instances. The CPU time increased sharply from 0.5 to 2490 seconds by increasing the number of trains from 3 to 10 on 15 sections in the MIP solution. The mixed integer programming method did not find a solution where there were more than 10 trains. MIP is not applicable for many instances which include a large number of trains and sections such as (15,11), (15/12), (15/13), (20/8), (20/9), (20/10), (20/11), (20/12), (20/13), (20/14), (20/15), (25/8), (25/12), (30/8) and (30/12), while CP-hybrid techniques are applicable for all instances.

A MIP model is one where some of the decision variables are constrained to be integer values. However, integer variables may make an optimization problem non-convex, and therefore MIP is inapplicable to solve industry-scale cases. Memory and solution time may rise exponentially as you add more integer variables. For example, in MIP, the all-different constraints usually require a substantial set of *n* decision variables to assume a permutation (non-repeating ordering) of integers from 1 to *n*. In comparison, CP defines "higher-level" all-different constraints in a better way (i.e., less memory and solution time).

Table 1 shows that, of the metaheuristic techniques, the CP/TS and CP/SA improved the CP for the all tested instances. The CP/TS results are better than the CP/SA results for most of the tested instances and the CPU time when applying the CP/TS technique is shorter than CP/SA, although the CP/TS and CP/SA techniques have the same makespan for the most of 3 and 4 train instances except (15/3, 15/4, 20/3, 25/3 and 30/4).

For most of the 37 instances, the hybrid (CP-TS/SA) finds the best solutions with the minimum makespan and the lowest CPU time. The CPU time was increased relatively consistently with the number of sections and the number of trains using the hybrid (CP-TS/SA) solution technique. As a result, solutions can be obtained for large instances without requiring more computing resources. Two main insights based on the results of Table 1 can be concluded as follows. First, it is observed that an optimal solution by MIP can easily be produced for the small instances in a short time. However, MIP becomes time consuming for solving large instances that include a large number of trains and sections and cannot be used to solve many instances. In comparison, CP used as an initial solution for the hybrid techniques and can used as a good start point. As a result, integrating CP with metaheuristic solution techniques improved the solutions of hybrid techniques in a reasonable time. Second, among the different solution approaches, the hybrid (CP-TS/SA) is the best with the ideal optimality performance and the lowest CPU time.

Table 1: Comparisons of different techniques to solve sugarcane train scheduling problem

Test ($s_{i/k}$)	# of Variables (MIP)	# of Constraints (MIP)	# of Variables (CP)	# of Constraints (CP)	MIP-CPLEX Optimal		CP	CP/TS		CP/SA		Hybrid(TS/SA)		Hybrid (CP-TS/SA)	
					C_{max}	CPU (s)	C_{max}	C_{max}	CPU (s)	C_{max}	CPU (s)	C_{max}	CPU (s)	C_{max}	CPU (s)
10/3	3127	40123	3001	31295	8760	0.25	9823	8984	18	9004	20	9029	12	8815	10
10/4	3980	44234	3820	34502	9810	.5	10249	9820	31	9830	55	9830	37	9820	28
10/5	4570	53678	4387	41868	11567	6	12630	12131	50	12222	79	12098	38	11898	32
10/6	5890	6345	5654	4949	13456	88	14050	13752	74	13810	101	13902	59	13562	45
10/7	7145	89136	6859	69526	14768	145	15500	15182	95	15231	135	14818	75	14790	65
10/8	8790	112345	8438	87629	15689	290	17150	16140	120	16534	160	16052	81	15802	73
15/3	3823	49345	2102	39969	9900	.5	10943	10430	23	10430	62	10600	29	10100	15
15/4	4625	54464	2543	44115	11525	0.66	12334	12017	49	12067	88	12167	51	11620	38
15/5	5678	77675	3122	62916	13890	123	15320	14653	69	14850	95	14376	71	13986	51
15/6	6954	94567	3824	76599	14800	289	16234	15732	89	15943	145	15680	102	15013	65
15/7	8120	129125	4466	104591	15980	457	17745	17044	118	17252	170	17052	142	16622	87
15/8	10689	166528	5878	134887	16688	774	18650	17822	149	18023	205	18030	164	17220	105
15/9	12160	201114	6688	162902	19161	1523	21270	20199	175	20351	244	20132	205	19311	137
15/10	14230	242197	7826	196179	20150	2490	22980	22155	203	22273	288	22266	223	20435	156
15/11	16191	291232	8905	235897	n/a	n/a	24180	23316	226	23610	304	23370	240	22580	186
15/12	18193	344112	10006	278730	n/a	n/a	25395	24256	254	24416	328	24691	251	23631	209
15/13	21670	412345	11918	333999	n/a	n/a	27760	26831	287	27210	356	26772	270	26142	229
20/3	5120	67189	4812	56438	12190	1	12876	12432	32	12432	80	12496	37	12200	21
20/4	7765	96624	7299	81164	12522	1.67	14100	13630	73	13731	110	13935	83	13588	45
20/5	9128	142890	8580	120027	14930	230	17071	16149	100	16512	146	16148	147	15290	68
20/6	11890	187908	11176	157842	16450	450	18230	17490	130	17688	188	17267	205	16567	111
20/7	13256	210450	12460	176778	17650	879	19345	18604	180	18725	266	18830	223	17830	151
20/8	17449	295648	16402	248344	n/a	n/a	20145	19411	226	19645	302	19481	231	18699	192
20/9	20178	345923	18967	290575	n/a	n/a	22910	22280	270	22610	340	21590	251	21120	208
20/10	23567	434675	22152	365127	n/a	n/a	24255	23254	310	23600	390	23405	286	22146	249
20/11	26897	564545	25283	474217	n/a	n/a	25896	24688	370	24900	445	25388	282	24100	290
20/12	29053	607632	27309	510410	n/a	n/a	26990	25980	445	26100	501	25962	402	25134	355
20/13	33456	846734	31448	711256	n/a	n/a	28515	27110	489	27450	539	26882	445	26346	390
20/14	37678	1061231	35417	891434	n/a	n/a	30050	28857	540	29134	570	28053	499	27768	450
20/15	41234	1211123	38759	1017343	n/a	n/a	32881	31113	590	31720	630	30183	523	29567	482
25/3	8123	98134	7586	86357	15660	2	16190	15744	48	15744	84	15660	69	15700	44
25/4	11705	150784	10932	132689	17203	2.11	18044	17400	99	17412	140	17824	96	17300	55
25/8	25809	467168	24105	411107	n/a	n/a	24308	22867	300	23203	350	23645	282	22505	230
25/12	42313	945552	39520	832085	n/a	n/a	31320	29810	501	30122	600	30193	449	29370	395
30/4	16445	216944	15293	197419	22136	3.39	23024	22617	130	22617	180	22810	122	22166	86
30/8	35769	671008	33265	610617	n/a	n/a	29410	28100	399	28390	420	28561	905	27490	290
30/12	57973	1357872	53914	1235663	n/a	n/a	36220	35040	597	35200	690	35002	1451	34600	480

5. Conclusion

The sugarcane railway operations are very complex because of its dynamic nature. The proposed scheduling model has a huge number of variables and constraints as shown in Table 1 for different cases and needs to be solved in a reasonable time. Makespan is investigated using different number of trains and sections.

In this paper, a new and innovative mathematical model was presented for the sugarcane rail scheduling problem using CP approach under limited siding capacity and main sugarcane rail procedure which is proposed to optimise the activities of delivery and collection the harvester delay time. Metaheuristic techniques, SA and TS, adapted and integrated with CP to solve the sugarcane rail scheduling problem. For more accurate solutions and less CPU time in solving large size practical cases, new hybrid techniques developed is satisfactory in real-world implementations.

Regarding the future research directions, more dynamic and stochastic elements such as new arrivals of demands will be considered and incorporated in a reactive sugarcane railway scheduling problem.

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