

A DECISION SUPPORT SYSTEM FOR INTERMODAL TRAIN PLANNING

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ABSTRACT

Train planning is the process of assigning containers to certain wagons on an intermodal train. Currently, there is limited decision support used for train planning in Australia leading to costly rehandles when loading trains. Intermodal terminals are highly integrated systems that create a difficult planning environment for computerised decision support systems. We have addressed this difficulty for the specific problem of train planning by developing a detailed mathematical optimisation model. This paper describes the model and how it was implemented within a software system called ITP - Intermodal Train Planner. Numerical experiments are presented to demonstrate the effectiveness of ITP.

Key Words: Optimisation, Intermodal terminals, Train Planning, Decision support systems

1. INTRODUCTION

Intermodal transportation can be defined as the movement of goods in the same load carrying unit, which successively use several transport modes without handling of goods under transit (Ludvigsen, 1999). One of the most common types of intermodal transport involves the movement of containerised goods by a combination of rail and road. For example, a shipper will send containers by trucks to an intermodal terminal where the containers will be transferred onto a train. The train will carry the containers over the longest part of their journey and will arrive at an intermodal terminal in the destination city. The containers are then transferred onto trucks and delivered to their respective consignees.





Figure 1. The transhipment area of a simple intermodal terminal with three transhipment tracks and two gantry cranes.

The overall efficiency of this type of intermodal transportation is highly dependent on the capacity and operational efficiency of intermodal terminals. Figure 1 gives a simple illustration of how a typical intermodal terminal operates. Rail-wagons are positioned onto transhipment tracks which are serviced by container handling equipment such as gantry cranes. Trucks park adjacent to the transhipment tracks and containers are transferred back and forth between wagons and trucks. Transfers can be made directly between trucks and wagons but sometimes containers are placed in intermediate storage for several hours.

Intermodal transportation represents a cost effective and energy efficient alternative to long haul road transportation. Currently in Australia, there are 76 intermodal terminals with collective revenue of \$200 million per year. There is an opportunity to significantly improve the performance of intermodal terminals through the introduction of real time decision support and eventually autonomous handling equipment.

When compared to seaports in Australia, intermodal terminals have been slow to adopt new technologies. For example, several seaports are currently trialling the use of robotic straddle carriers and automatic guided vehicles. On the contrary, Australian intermodal terminals run manually operated handling equipment with almost all operational decisions made intuitively by the handling equipment operators.

There are several reasons for the slow uptake of new technology. The crux of the issue is that intermodal terminals are generally more chaotic environments than seaports and it is more difficult for computers to predict the outcomes of their decisions.

The authors of this paper are continuing to develop mathematical models that can be used to predict and optimise terminal operations. Several publications have resulted from this work so far, (Corry & Kozan, 2004, Corry & Kozan, 2005a, Corry & Kozan, 2005b, Kozan, 1997, Kozan, 2000). In this paper we will describe how some of the earlier work (Corry & Kozan, 2005b) has been elaborated and implemented as a decision support system for intermodal terminals. In particular, we are focusing on the problem of *train planning* which decides the positions of containers on a train.

The following section of this paper outlines international research which relates to the topic of train planning. This is followed by a detailed definition of the considered train planning problem and the proposed mathematical model. Solution techniques are discussed briefly, followed by a description of the software we have developed which is called *Intermodal Train Planner* (ITP). Numerical results are presented to demonstrate the software and followed by concluding remarks.

2. RELATED RESEARCH

Intermodal transport is emerging as a research field in its own right (Bontekoning et al., 2004). Recently, two studies have been published which comprehensively review the literature on intermodal terminals (Bontekoning et al., 2004, Marcharis & Bontekoning, 2004). Although there has been several studies relating to train planning, most of them deal with transportation systems which are uncommon in Australia.



In USA, a form of intermodal transportation called "piggybacking" is used. Piggyback systems transport the entire container and road trailer assembly over rail. Two studies (Feo & Gonzalez-Velrade, 1995, Powell & Carvalho, 1998) have considered the problem of train planning in a "piggyback" system. There objective was to maximise the utilisation of trailer hitches on the wagons.

Another study (Bostel & Dejax, 1998) considers a rail-to-rail transfer facility. These facilities are located at major intersections of the rail network and provide a means for interchanging containers from one train to another. The study proposes a model to determine optimum locations of containers on trains and short term storage to minimise handling time. A major limitation of the model is that it assumes a highly standardised system where containers can be treated as being of equal size.

In the following sections, we will describe a train planning model which is geared towards Australian intermodal transportation. Many factors are taken into consideration by the model including various container and wagon specifications, dangerous goods and drawgear capacities as well as other operational considerations.

3. TRAIN PLANNING

In this section we describe a particular version of the train planning problem. Most aspects of what is described here can be modified to meet the needs of terminals with different requirements. Here we consider a given a sequence of wagons for a particular train, and a given set of containers booked on that train. A train plan must be developed such that operational constraints are satisfied and two objectives are considered.

The first and most important objective is to minimise the number of wagons used. This minimises the total mass of the train which minimises energy consumption and mechanical stress. The secondary objective is to have the centre-of-mass of the loaded train as close as possible towards the front. At the joints between wagons, this minimises tension under acceleration and compression under braking thereby minimising mechanical stress.

When devising a train plan it is important to recognise that each type of wagon can be loaded in certain configurations of container classes. Some wagons can accommodate configurations that other wagons cannot. It is therefore necessary to know for each type of wagon exactly what configurations are allowed. Figure 2 illustrates some allowable configurations of container classes for a hypothetical class of wagon.





Figure 2. Example of allowable configurations for a given wagon (Corry & Kozan, 2005b).

There are several operational constraints to be considered when train planning.

- gross mass limits each wagon has a limit to its total gross mass;
- draw gear capacities each wagon has a limit to the total mass trailing behind;
- *height limit* there is a height limit on each rail corridor, tops of containers cannot exceed this height when loaded;
- refrigerated containers must be loaded onto wagons designed to accommodate them;
- *dangerous goods* must be separated by minimum distances and must be separated from certain classes of wagon; and
- *destination blocks* containers must be loaded into contiguous blocks ordered by destination, the first destination block at the rear and final destination block at the front.

The train planning problem considered in this paper is adapted from that proposed in the earlier study (Corry & Kozan, 2005b). The earlier study considered dynamic train planning where decisions are made in real-time to minimise the handling time required to load the train. Because of the complexity and volume of real-time data required for dynamic train planning, further development into viable software is an ongoing issue.

In this study we consider a static version of train planning where trains are pre-planned and are loaded according to the fixed train plan. Compared to dynamic train planning, the static system is far less costly to produce and implement and so provides a bridging step towards the more difficult dynamic train planning.

Although many terminals require dynamic train planning, there are still applications for static train planning. A static train plan can be used as a guide when loading a train rather than a strict plan. Another application is in the container booking process. A static train plan can be developed each time a container is booked to ensure that enough wagon space is available. Finally, some terminals receive all containers to storage before loading the train. Static train planning is ideal for this type of system.



4. OPTIMISATION MODEL

The train planning optimisation model implemented in the ITP software is given below.

Indices

j, k wagon indices, note that wagons are indexed according to their position in the train sequence $j, k = 1, ..., n_{wgn}$

a configuration index, $a = 1, ..., n_{cfg}$

h, i container indices, $h, i = 1, ..., n_{ctr}$

p container class index, $p = 1, ..., n_{cl}$

Variables

 C_{ja} = 1 if configuration *a* assigned to wagon *j*, 0 otherwise

 $U_{ij} = 1$ if container *i* is assigned to wagon *j*, 0 otherwise

N number of wagons utilised

Parameters

 $q_{ja} = 1$ if configuration *a* is allowed for wagon *j*

 s_{ap} number of slots for containers of type p in configuration a

 $r_{ip} = 1$ if container *i* is a class *p* container, 0 otherwise ($\Sigma_p r_{ip} = 1$)

Other Notation

 $C(\mathbf{U})$ position of loaded train centre-of-mass as a proportion of total train length $0 < C(\mathbf{U}) < 1$

 $\gamma_{1,\gamma_{2}}$ scaling coefficients for wagons used and centre-of-mass respectively

 $P_{v}(\mathbf{U}) \quad v^{\text{th}}$ penalty function where U_{ij} is the j^{th} element in the i^{th} row of \mathbf{U}

 λ_{v} scaling coefficient for the v^{th} penalty function

Model

$$\min \gamma_1 N + \gamma_2 C(\mathbf{U}) + \sum_{\nu=1}^7 \lambda_{\nu} P_{\nu}(\mathbf{U})$$
(1)

Subject to

 $\sum_{a} C_{ja} \le 1 \qquad \qquad \forall j \qquad (2)$

$$C_{ja} \le q_{ja} \tag{3}$$

$$\sum_{j} U_{ij} = 1 \qquad \qquad \forall i \qquad (4)$$

$$\sum_{a} s_{ap} C_{ja} = \sum_{i} r_{ip} U_{ij} \qquad \forall j, \forall p$$
(5)

$$N \ge \sum_{a} jC_{ja} \qquad \forall j \qquad (6)$$



The objective function (1) consists of three components. The first component minimises the number of wagons used for the train. The second component minimises the centre-ofmass of the train meaning that the heaviest containers should be towards the front of the train. The third component minimises seven penalty functions which correspond to soft constraints representing the operational constraints discussed earlier. Before discussing the details of these penalty functions, we will first describe constraints (2) through (6).

Constraint (2) ensures that wagons are assigned at most one configuration. If no configuration is assigned to a given wagon, then that wagon will run empty. Constraint (3) prevents wagons from being assigned configurations that are not allowed. Constraint (4) ensures that containers are assigned to exactly one wagon. On each wagon, constraint (5) enforces a balance between the number of slots available and the number of assigned containers for each container class.

The proposed model is different from earlier work into train planning. The number of variables has been significantly reduced by considering the assignment of containers to wagons rather than assignment to particular slots on wagons. The trade-off for this reduction in variables is that some approximations are necessary when determining whether dangerous goods constraints are satisfied. These issues are discussed later in this section. Another point of difference has been the inclusion of centre-of-mass into the objective function.

The following subsections describe the centre-of-mass function and penalty functions shown in the objective function (1). Most of these penalty functions include expressions of the form $\sum_{i} \max(0, f_i(\mathbf{U}))$. Although these expressions are not shown in linear form, it is trivial to do so by introducing a set of variables, for example, f_i^+ where $f_i^+ \ge 0$ and $f_i^+ \ge f_i(\mathbf{U})$ for all *i*. The expression then becomes $\sum_i f_i^+$.

The final point to note regarding these penalties is that intermodal transport systems in various regions operate under different operation requirements. The penalty functions can easily be adapted as necessary.

Centre-of-Mass

Equation (7) describes how centre-of-mass is calculated. This is a one dimensional formulation which models the train's mass distribution as a series of point masses acting at the mid-points of wagons. Each point has the mass equal to the gross mass of its corresponding wagon. Parameters required to calculate (7) include: m_j^w is the empty mass of wagon *j*; m_i is the mass of container *i*; \bar{x}_j is the midpoint of wagon *j* measured from the front of the train; and *L* is the train length.

$$C(\mathbf{U}) = \frac{\sum_{j} \left[\overline{x}_{j} \left(m_{j}^{w} + \sum_{i} m_{i} U_{ij} \right) \right]}{L \left(\sum_{j} m_{j}^{w} + \sum_{i} m_{i} \right)}$$
(7)

The scaling coefficient 1/L ensures that $C(\mathbf{U})$ takes a value between 0 and 1. If the centre-of-mass was half way along the train then $C(\mathbf{U}) = 0.5$. If the centre-of-mass was in the front half of the train then $C(\mathbf{U})<0.5$. Conversely, if the centre-of-mass was in the rear half of the train then $C(\mathbf{U})>0.5$.



Gross Mass Limits

The first penalty function (8) determines the total mass in violation of wagon mass limits. An additional parameter required to calculate this penalty is m_j^{max} – gross mass limit of wagon *j*.

$$P_1(\mathbf{U}) = \sum_j \max\left(0, m_j^w + \sum_i m_i U_{ij} - m_j^{\max}\right)$$
(8)

Draw Gear Capacities

Draw gear capacity is represented by the second penalty function (9). It calculates the total trailing mass exceeding draw gear capacity for each wagon. The parameter g_j represents the draw gear capacity for wagon j. Note that the trailing mass for a given wagon is inclusive of the wagon's own gross mass.

The trailing mass does not include empty wagons at the end of the train because these wagons are not needed and will not be attached to the train. This is accomplished with the variable α_j which equals one if *j* is utilised and zero otherwise. Constraints (10) and (11) enforce the correct value for α_j .

$$P_{2}(\mathbf{U}) = \sum_{j} \max\left(0, \sum_{k\geq j} \left[m_{k}^{w}\alpha_{k} + \sum_{i} m_{i}U_{ik}\right] - g_{j}\right)$$
(9)

$$N+1 \le j + M\alpha_j \qquad \qquad \forall j \qquad (10)$$

$$j \le N + M(1 - \alpha_j) \qquad \qquad \forall j \qquad (11)$$

Height Limit

Rail corridor height limit is represented by the third penalty function (12). The height of each container, $h_{i,}$ is added to the deck height of the wagon h_j^w it is assigned to. If this total height exceeds the height limit, h_{max} , then the excess is added to the penalty function.

$$P_{3}(\mathbf{U}) = \sum_{i} \max(0, h_{i} + \sum_{j} h_{j}^{w} U_{ij} - h_{\max})$$
(12)

Refrigerated Containers

Matching refrigerated containers to appropriate wagons is achieved by the fourth penalty function (13). The parameter f_{ij} equals one if container *i* should not be loaded onto wagon *j*, zero otherwise.

$$P_4(\mathbf{U}) = \sum_i \sum_j f_{ij} U_{ij}$$
(13)

Dangerous Goods

There are two penalty functions (14) and (17) that enforce the minimum separations of dangerous goods. The first penalty function enforces the minimum separation d_{ih} between containers *i* and *h*. Parameters x_k represent the position corresponding to the front of wagon *k* and the rear of wagon k - 1 and x_0 equals zero. Note that for calculation of wagon midpoints in (7), $\overline{x}_i = (x_i + x_{i+1})/2$ and $L = x_{(n_{wag}+1)}$.



Assume that container *i* is assigned to wagon *j* and container *h* is assigned to wagon *k* which is behind *j*, that is, $U_{ij} = 1$, $U_{hk} = 1$ and $x_{j+1} \le x_k$. The separation between containers *i* and *h* is taken to be the distance between the front of wagon *k* and the rear of wagon *j*, i.e. $x_k - x_{j+1}$.

This distance is an underestimate of the actual separation between containers i and h because it does not account for actual their positions within the deck space of the wagons. The true distance cannot be determined within the proposed model. Container positions within deck spaces are not considered here in order to minimise the number of variables. This is a particular point of difference with earlier work (Corry & Kozan, 2005b) which does consider the exact positions of containers on wagons. For the static train planning problem considered here, the benefit of including this level detail is outweighed by the significant increase in the number of parameters and variables.

In the penalty function below (14), there are three arguments to the max function. The first returns zero if containers *i* and *h* are separated by more than the minimum distance d_{ih} . The second two arguments return the total separation distance in violation of the minimum requirement. In particular, the second term will be returned if container *h* is in front of *i* on the train and the third term will be returned if *h* is behind *i*.

$$P_{5}(\mathbf{U}) = \sum_{i} \sum_{h>i} \max \begin{pmatrix} 0, \\ d_{ih} - \left(\sum_{k} x_{k} U_{hk} - \sum_{j} x_{j+1} U_{ij}\right) - M(1 - \beta_{ih}), \\ d_{ih} - \left(\sum_{j} x_{j} U_{ij} - \sum_{k} x_{k+1} U_{hk}\right) - M\beta_{ih} \end{pmatrix}$$
(14)

Note that a new set of binary variables has been introduced in (14). β_{ih} equals one if container *i* is assigned to a wagon in front of container *h* and β_{ih} equals zero otherwise. The following constraints enforce the correct relationship between β_{ih} and the decision variables. Note that the index range of these constraints includes a reference to the parameter b_{ih} . This parameter is unrelated to dangerous goods but relates to the seventh penalty function which also requires (15) and (16).

$$\sum_{j} (j+1)U_{ij} \leq \sum_{k} kU_{hk} + M(1-\beta_{ih}) \qquad \forall i,h: (h>i,d_{ih}>0 \lor b_{ih}=1)$$
(15)
$$\sum_{k} kU_{hk} \leq \sum_{j} jU_{ij} + M\beta_{ih} \qquad \forall i,h: (h>i,d_{ih}>0 \lor b_{ih}=1)$$
(16)

The penalty function for separation between dangerous goods containers and specified wagons is given by (17). Again, the separation distance is an underestimate of what the true separation might be. The parameter d_{ij}^{w} defines the minimum required separation distance between container *i* and wagon *j*.

$$P_{6}(\mathbf{U}) = \sum_{i} \sum_{j} \max\left(0, d_{ij}^{w} - \sum_{k>j} (x_{k} - x_{j+1})U_{ik} - \sum_{k(17)$$



Destination Blocks

Loading containers within destination blocks is enforced by (18). The parameter b_{ih} equals one if container *h* should be loaded onto a wagon to the rear of container *i*. Note that the variables β_{ih} from constraints (15) and (16) are used in (18). For a given pair of containers *i* and *h*, a penalty of one is added if container *h* must be behind container *i* ($b_{ih} = 1$) but does not satisfy this requirement ($\beta_{ih} = 0$).

$$P_{7}(\mathbf{U}) = \sum_{i} \sum_{h \neq i} b_{ih} (1 - \beta_{ih})$$
(18)

5. SOLUTION TECHNIQUES

A variety of solution techniques have been developed to obtain near-optimal train plans. This section outlines the techniques and describes the pros and cons of each. The techniques used include branch and cut, a constructive heuristic, local search and simulated annealing. Branch and cut was performed using commercial software. The local search and simulated annealing heuristics were adapted from a previous study (Corry & Kozan, 2005b).

Preliminary experiments found that local search performed poorly when starting from an initial solution consisting of all empty wagons. To improve this situation, we propose a constructive heuristic to provide an initial solution. Using the constructed initial solutions was found to significantly improve the solutions obtained by local search and in significantly less time.

Branch and Cut (BC)

Commercial software called Ilog Cplex Concert Technology (ILOG, 2003) employs a branch and cut algorithm to obtain optimal or near optimal solutions to mixed-integer programming problems. Cplex was used in this study as a benchmark to evaluate the proposed heuristics where possible.

Preliminary experimentation found that for a problem with 115 containers all having the same destination, solutions could be found within minutes. However, when there were two possible destinations for containers, no feasible solution was obtained within 16 hours. This is because of the large number of additional β_{ih} variables required for (18). Assuming 57 containers for one destination and 58 for the other, an additional 3306 β_{ih} variables are required and this number increases with the number of destinations.

Cplex allows the user to set a parameter for the MIP gap tolerance. For this study, the tolerance was set to the default value of 0.01%. This means that the search was terminated when the best integer solution was within 0.01% of the best known lower bound. We can therefore say with certainty that any quoted Cplex solutions are within 0.01% of the optimal solution. It was found that using a tolerance of 0% often caused a ten fold increase in CPU time.

Constructive Heuristic (CH)

A constructive heuristic was developed to provide reasonably good initial solutions for local search. There are two phases to the heuristic. The first phase determines wagon configurations and the second phase determines the container-wagon assignments. The first phase of the heuristic works as follows.



- Start by determining the number of containers in each container class booked on the train, i.e. $n_p = \sum_i r_{ip}, \forall p$, Set j = 1 and proceed to step 2.
- Add up the total length of containers carried in each allowable configuration for wagon *j*.
- Assign the configuration *a* with greatest total container length such that there are sufficient booked containers to occupy the class slots in the configuration, i.e. $s_{ap} \le n_p, \forall p$.
- Decrement the number of containers in each class by the number of class slots in the assigned configuration, i.e. $n_p = n_p s_{ap}$, $\forall p$.
- If $j = n_{wgn}$ then stop, else set j = j + 1 and go to step 2.

The second phase of the heuristic sorts the container classes by destination then mass, and assigns them from front to back of the train accordingly.

- For each container class *p*, sort the containers by destination then mass.
- For each wagon *j*, assign the next unassigned containers matching the class slots of the configuration for wagon *j*.

Note that in the first phase, there may not be an allowable configuration for the last wagon $j = n_{wgn}$ that precisely matches the mix of remaining containers. This would cause an imbalance between the number of containers and slots for each class which violates constraints (4) and (5). Although the constructive heuristic cannot guarantee a feasible solution, a new penalty function (19) is introduced so that local search and simulated annealing can resolve this infeasibility. This penalty function determines to total imbalance between slots and containers for each container class.

Note that (19) contains an absolute value operator which creates non-linearity. There is no need to linearise this expression because the heuristics can accommodate non-linearity. Also note that (19) is not included for the branch and cut procedure because constraints (4) and (5) are used instead.

$$P_8(\mathbf{U}) = \sum_p \left[\sum_j \left| \sum_a s_{ap} C_{ja} - \sum_i r_{ip} U_{ij} \right| \right]$$
(19)

Local Search (LS)

Local search is a steepest descent approach for combinatorial problems. The following procedure describes the LS procedure used in this study.

- Apply CH to get an initial solution.
- If all possible neighbours to the current solution have been examined then stop, else generate a new neighbour to the current solution.
- If the new neighbour improves the current solution then set the current solution to be the neighbour and go to step 2

Shortly we will describe the neighbourhood for LS which was first proposed in the previous study (Corry & Kozan, 2005b). But first we will describe the two main points of difference between the above procedure and the earlier work. Firstly the method of finding an initial solution is new. This is reflects the change from dynamic to static train planning and



also eliminates the reliance third party software which was used to produce initial solutions in the previous study.

Secondly, the previous study replaced steps 2 and 3 by selecting the best of all possible neighbours. This suits dynamic train planning because only small changes are made from one train plan revision to the next. However, preliminary experiments found this approach to be too slow for static train planning because of the large neighbourhood size and lesser quality of the initial solution.

The neighbourhood used in LS consists of two parts, one for wagon configurations and another for container assignments. The wagon configuration neighbourhood operator alters the wagon configurations assigned to two different wagons. If the current solution is balanced in terms of container classes and slots then this neighbourhood is restricted to exchanges that maintain the balance. Say for example that wagon *j* moves from configuration *a* to configuration *b* and wagon *k* moves from *c* to *d*. Then we would have $s_{ap} + s_{cp} = s_{bp} + s_{dp}$, $\forall p$.

The second part of the neighbourhood uses a sequence of containers for each container class to determine container wagon assignments. This is similar to the second phase of CH described earlier. The neighbourhood operator exchanges two containers of the same class within their corresponding container class sequence. This has the result of exchanging the wagons assigned between the two containers.

Simulated Annealing (SA)

Simulated annealing (Kirkpatrick et al., 1983) was applied essentially unchanged from what was proposed in (Corry & Kozan, 2005b). One point of difference is that here LS is used to provide an initial solution. A standard geometric cooling schedule was used with the following control parameters: T_0 – initial temperature; f – cooling factor; s – number of temperature steps; and n_{it} – number of iterations. The same neighbourhood operators as LS are used. A configuration exchange is selected at random with probability 0.75 and a container sequence exchange is selected at random with probability 0.25. This arrangement was found to be suitable in preliminary experiments. The other control parameters were also tuned during preliminary experiments and the following values were found to produce good results for the problems tested, $T_0 = 100$, s = 1500, f = 0.98 and $n_{it} = 150000$.

6. ITP SOFTWARE

The main purpose of this study was to evaluate the best solution techniques to be implemented within software called Intermodal Train Planner – ITP. There are two distinct but related components that make up the ITP software. The first of these components is a Microsoft Access database for holding and maintaining all the data relevant to train planning. The second component is a Windows application controlled by a graphical user interface. It executes the proposed heuristics to generate feasible and efficient train plans.

Users interact with both components of the system. The windows application retrieves data from the database and presents its output to the user. Figure 3 illustrates the relationships between ITP components and the user.





Figure 3. Architecture of ITP software.

The majority of data held in the database will change infrequently once it has been entered.

- Rail corridors and destinations
- Train departure schedules
- Dangerous goods separations
- Draw gear capacity data
- Wagon classes and wagons
- Allowable configurations of containers on wagons
- Container classes

The remaining data held in the database refers to weekly issues involving sequences of wagons assigned to trains and containers booked on trains.

- Sequences of wagons assigned to trains (may change infrequently for shuttle services)
- Containers booked on trains and specifications relating to their contents such as mass and dangerous goods class.

Data entered into the database is retrieved by the *ITP* windows application which applies CH, LS and optionally SA to develop train plans. This application was developed using Microsoft Visual C++ .Net. Figure 4 shows two screen shots of the application. Users interact with the controls displayed in the top portion of the window.



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Figure 4. Screen shots of ITP software, objective function analysis and train plan view.

The left most control is a drop down list from which containers the identifier codes of all trains recorded in the database. Users select which train they want to plan for and then click the "Optimise" button. This invokes the heuristics to develop a train plan.

Once optimisation is complete, users can click the "Report" button to view an objective function break-down for the incumbent train plan. This report shows the values obtained for each penalty component of the objective function. For non-zero penalties, further information is given so that users can identify which containers are causing the constraint violations.

Users can view the train plan by clicking the "View" button and the contents of the application window can be saved as a text file by clicking the "Save" button. Clicking the "Settings" button invokes the dialog box shown in Figure 5. This allows users to select between LS and SA, set control parameter values for SA and set objective coefficients for the various objectives and penalty functions. The settings shown in Figure 5 were those used during the numerical experiments of this study.



Figure 5. Dialog box for ITP settings.



7. NUMERICAL EXPERIMENTS

Some numerical experiments were performed to evaluate the performance of LS and SA. Comparisons were made on train planning problems with a variety of characteristics such as tightness of mass related constraints, numbers of dangerous goods containers and destinations. Further experimentation was performed to evaluate the use of the ITP software as a decision tool for booking containers onto trains. All experiments were performed on a PC with Pentium 2.4 GHz processor and 512 Mb RAM.

A sample train was developed by randomly generating a sequence consisting of 70 wagons with locomotive at the front. The wagon specifications and allowable configurations were taken from real data. The sample train was approximately 1200m in length which is common in Australia. Although the wagon sequence was randomly generated, it was done in such a way that wagons with larger draw-gear capacities were more likely to be sequenced towards the front of the train.

Additionally, 115 containers were assigned to the train. The mix of container classes was 1 x 4.9m, 74 x 6.1m, 6 x 7.6m, 29 x 12.2m, 3 x 13.8m and 2 x 14.7m. This type of mix is realistic for intermodal trains in Australia based on information gathered from industry experts. Masses of containers were randomly generated from a normal distribution with each container class having its own mean and variance.

Two sets of container masses were generated, one with heavier masses so that wagon mass limits and draw gear capacity constraints were tight, the other with lighter masses so that the constraints were loose. We will denote the two datasets 115T and 115L. Expression (20) is used as a measure of tightness for these constraints. This expression calculates the ratio of total gross mass of the loaded train and total gross mass capacity of the train. As *T* increases towards T = 1, it is more difficult to find a feasible train plan and for T > 1 it is impossible. For the two generated datasets we have $T_{115T} = 0.72$ and $T_{115L} = 0.46$.

$$T = \frac{\sum_{j} m_{j}^{w} + \sum_{i} m_{i}}{\sum_{j} m_{j}^{\max}}$$
(20)

The first experiment was an evaluation of LS, SA compared with Cplex solutions on 115L and 115T. No dangerous goods containers were to be planned and a single destination was assumed.

Table **1** shows the results of this experiment. For 115T the Cplex solution achieved was 68.4383 which can be interpreted as 68 wagons used with a centre-of-mass located 43.83% along the length of the train. The simulated annealing solutions were slightly worse than Cplex with centre-of-mass at 43.98%. Local search was significantly worse because of a violation of a gross wagon mass constraint resulting in a penalty. For the problem 115L, the reduced constraint tightness resulted in both local search and simulated annealing achieving the quality of the Cplex solution.

An interesting observation from

Table 1 is that the CPU times of simulated annealing were about 4.5 minutes longer than Cplex. For these two problems the branch and cut procedure of Cplex was successful but further experimentation found that its advantage was eliminated when destination blocks and



dangerous goods containers were included. This is when simulated annealing becomes the technique of choice.

The second series of experiments evaluated the solution techniques on problem 115T with varying numbers of dangerous goods containers. For each problem instance the dangerous goods containers were assigned randomly out of the set of 115 containers. The required separations were 12.2m between dangerous goods containers and 24.4m from the locomotive at the front of the train. Table 2 shows the results of this experiment. Cplex solutions were not obtained for problems with 30 or more dangerous goods containers. This is because the optimality gap was greater than 50% after 16 hours of run time at which point the execution was terminated. Simulated annealing was again very competitive with the Cplex solutions. Local search failed to find a solution without constraint violation penalties with exception of 115T- 15dg.

The next series of experiments evaluated the solution techniques for varying numbers of destinations. Container destinations were selected randomly with equal probabilities. Cplex was unable to attain solutions of reasonable quality within 16 hours so they are not shown.

Table 3 shows that local search performed inconsistently compared with simulated annealing. The first problem that was tested was 115T with 2 destinations. None of the solutions obtained were without constraint penalties which included violations of wagon mass limits, draw capacities and destination blocks. The remaining problems tested were all variants of 115L. Simulated annealing began to falter on the 5 destination problem where it achieved zero constraint penalties only once out of three runs.

The final experiment investigated using the proposed model as a tool for deciding whether to accept or reject container bookings. A container booking would be rejected (or booked on another service) if it was infeasible or unsafe include the container into the current train consist.

Problem	Cplex	LS	SA avg	SA 1	SA 2	SA 3
115T	68.4383	147.3961	68.4398	68.4399	68.4397	68.4398
Z / Zbest	1	2.153707	1.000022	1.000023	1.00002	1.000022
CPU (s)	(67)	(61)	(299)	(278)	(309)	(309)
115L	68.4555	68.4556	68.4555	68.4555	68.4555	68.4555
Z / Zbest	1	1.000002	1	1	1	1
CPU (s)	(17)	(86)	(295)	(296)	(295)	(294)

Table 1. Comparison of solutions obtained for two single destination problems with no dangerous goods containers.

Table 2. Comparison of solutions obtained for single destination problems with varying numbers of dangerous goods containers.

Problem	Cplex	LS	SA avg	SA 1	SA 2	SA 3
115T - 6dg	68.43833	381.2643	68.4389	68.4392	68.4385	68.439
Z / Zbest	1	5.570918	1.000008	1.000013	1.000002	1.00001



CPU (s)	(93)	(66)	(273)	(274)	(273)	(272)
115T - 15dg	68.43821	69.4454	68.44097	68.4405	68.4412	68.4412
Z / Zbest	1	1.014717	1.00004	1.000033	1.000044	1.000044
CPU (s)	(142)	(65)	(261)	(278)	(253)	(251)
115T - 30dg		4429.419	69.11203	68.4468	69.445	69.4443
Z / Zbest		64.71331	1.009719	1	1.014584	1.014573
CPU (s)		(54)	(247)	(247)	(247)	(247)
115T - 32dg		2901.226	616.2582	462.2433	383.2651	1003.266
Z / Zbest		7.569763	1.607916	1.206067	1	2.617682
CPU (s)		(56)	(249)	(246)	(245)	(255)

Table 3. Comparison of solutions obtained for problems with varying numbers of destinations.

Problem	LS	SA avg	SA 1	SA 2	SA 3
115T - 2 dest	976.7817	213.0801	146.413	146.4136	346.4137
	6.671414	1.455336	1	1.000004	2.366004
	(69)	(266)	(259)	(257)	(283)
115L - 2 dest	68.472	68.472	68.472	68.472	68.472
	1	1	1	1	1
	(84)	(288)	(300)	(298)	(266)
115L - 3 dest	170.4831	103.1481	170.4831	69.4804	69.4807
	2.453686	1.484564	2.453686	1	1.000004
	(101)	(314)	(315)	(313)	(313)
115L - 4 dest	69.4807	69.4807	69.4807	69.4807	69.4807
	1	1	1	1	1
	(100)	(313)	(315)	(312)	(312)
115L - 5 dest	4168.461	136.8343	71.5062	168.4925	170.5043
	59.12727	1.940918	1.014275	2.389971	2.418508
	(122)	(333)	(334)	(333)	(332)



	115T	+ 14.7m	+ 6.1m	+ 12.2m	+ 12.2m	+ 12.2m
Cplex	68.43831	69.4426	69.4435	70.4461	71.4508	infeasible
	(67)	(52)	(48)	(48)	(51)	(10)
SA	68.4397	69.4425	69.4423	71.4468	infeasible	infeasible
	(309)	(297)	(305)	(288)	(705)	(317)

Table 4. Comparison of SA and Cplex when extra containers are added to problem 115T.

Table 5. Comparison of SA and Cplex when extra containers are added to problem 115T.

	115T	+ 6.1m	+ 6.1m	+ 7.6m	+ 6.1m	+ 12.2m	+ 12.2m	+ 6.1m
Cplex	68.43831	68.4401	69.4421	69.4446	70.4445	17.4481	infeasible	71.448
	(67)	(50)	(77)	(52)	(66)	(51)	(9)	(74)
SA	68.4397	68.44	69.4425	70.4499	70.4433	71.4483	infeasible	149.3988
	(309)	(318)	(297)	(308)	(325)	(333)	(348)	(340)

The experiment began with problem 115T and added randomly generated containers one-byone until it was infeasible to add any more. This experiment was performed twice with different containers generated each time. There were no dangerous goods containers included and a single destination was assumed which allowed Cplex to be used as a benchmark.

Table 4 shows the results of the first half of the experiment. From the Cplex results, it can be seen that a maximum of 119 containers could feasibly be loaded onto the train. Although it is not shown in Table 4, further attempted bookings of smaller containers were also rejected. Simulated annealing accepted the bookings of 118 containers, one less than Cplex.

Table 5 shows the second half of the experiment. Here the extra containers were shorter in length than in Table 4 so that more bookings could be accepted. Using Cplex, a total of 121 container bookings were accepted. Note that after the final 12.2 m container was rejected, there was still room for one more 6.1 m container. Simulated annealing accepted a total of 120 container bookings. Although the final 6.1 m booking was feasible, constraint violations meant the booking was unsafe. Cplex however found that the 6.1 m container could be safely included into the train consist.

8. CONCLUSION

This study has proposed a model for pre-planning the arrangement of containers on intermodal terminals to achieve maximum wagon utilisation and optimum weight distribution within the bounds of physical and safety constraints. The proposed methodologies have been implemented within a decision support system which includes a database and user interface.

Experiments were conducted to evaluate the system under two different applications, train pre-planning and as a decision tool for accepting or rejecting container bookings. It was demonstrated that simulated annealing performed well compared with benchmarks obtained using Cplex. Local search was found to perform inconsistently over the range of problems tested. Computation times of about five minutes for simulated annealing are quite acceptable for the task of train pre-planning. However, for container bookings this should be reduced to



about 30 seconds. Further research and improvements in processor speed will see this benchmark achieved in the near future.

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