IDENTIFYING THE FLEET MIX IN A MILITARY SETTING

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ABSTRACT

When assessing land vehicle fleet capabilities in off-shore military operations, it is necessary to develop and apply a reliable mechanism for creating and testing different fleet structures. In this paper, we introduce a vehicle fleet mix problem under military environment, discuss the complexity of the problem and present a fleet-optimization system for deciding an appropriate vehicle fleet mix by optimizing multiple objectives while satisfying the system constraints. The system is based on a number of heuristics that can answer a number of key questions required for long term capability planning such as utilization of current fleet, mix of different vehicle and modular units for a given scenario, and overall fleet structure. We demonstrate the effectiveness of our system through a case study based on a simple example dataset.

Key Words: *Vehicle Modularisation, Heuristics-Based Fleet Optimisation, Fleet Scheduling.*

1. INTRODUCTION

The overall operational success of any military force is heavily dependent on its degree of mobility and its capacity to sustain prolonged off-shore deployments. To a large degree both mobility and sustainability can be derived from the capability of the force’s fleet of vehicles. The requirement for a capable vehicle fleet is most acute in the environments of land-based military forces that often call for a large number of vehicle assets from a range of functional types, to meet a wide variety of mobility and sustainment tasks. Many operational aspects need to be considered when deciding on the most appropriate vehicle employment.

Vehicle fleets for large organisations, such as land-based military forces, are significant contributors to operational effectiveness and efficiency. They invariably entail a sizeable, long-term, and wide ranging investment of both capital and operating funds. Thus in organisations that require a core transport capability, such as land-based military forces, determining the optimal mix of vehicles represents key strategic decisions.

The strategic significance of optimising military vehicle fleets is matched by the complexity of the problem. Determining the mix of large heterogeneous transport fleets represents a difficult computational problem. Owing to its large-scale and combinatorial complexity, calculating an optimal fleet solution carries a heavy computational burden, and its realisation in an acceptable timeframe is very unlikely. As this is not considered an achievable goal, heuristic or approximation methods are often employed.

The strategic significance and complexity of these fleet mix optimisation problems therefore demand that decision makers have reliable mechanisms for creating and testing fleet options designed to undertake future military operations. While the subject of fleet mix optimisation has been studied in the context of commercial fleets and some military airlift fleets[**1**], there is no evidence that it has been examined in the context of purely land-based military vehicle fleets. The military land environment includes a number of operational constraints many of which have unique military dimensions. Amongst them are threats, risks and concomitant protection requirements, terrain limitations, load compatibility, maintenance requirements, task connectivity, convoy requirements, crew restrictions, tasking time windows, and occupational health and safety requirements. Additionally, military vehicle fleets confront a multitude of tasks, subsets of which may be isolated to a particular industry sector in the commercial domain. In this regard, examinations of fleet mix problems in the literature often are made with reference to one particular industry sector.

In this paper we will firstly describe vehicle modularisation in Australia's future military vehicle fleet (Section 2), and then, in Section 3, review some of the approaches and methods that have been applied to vehicle fleet optimisation problems. In the fourth section we present our heuristics-based solver system and then, in Section 5, apply it to a simple case study. In the final section we conclude.

Figure 1. Modular Vehicle with ISO Module and Integral Load Handling System[1]

Figure 2. Modular Vehicle with Integral Load Handling System and Modular Trailer both with Flat Rack Modules[2]

2. MODULARISATION OF MILITARY VEHICLES

The nature of the future military vehicle fleet examined in this paper we describe as 'modularised'. Incorporating both truck and trailer assets, the concept of a modularised vehicle fleet sees a basic truck and/or trailer combination configurable to a task specific variant, suitable for a particular payload or function, by the addition of an appropriate 'module'. Vehicles of a general cargo functional type, for example, should be configurable by the addition to a base vehicle of a flat rack[3], ISO container[4], bulk liquid tank, dump or tip-

[1] www.globalsecurity.org (accessed 27 July 2005)
[2] www.oshkoshtruck.co.uk (accessed 27 July 2005)
[3] A type of demountable truck tray to carry cargo loads
[4] Shipping Container compliant with standards promulgated by the International Organization for Standardization

truck module. Other vehicle functional types also employ this modularised capability. The concept of utilising modules is designed to divorce the payload task functionality from the generic vehicle. Additionally, the notion is that with common interfaces, system components can be designed so that vehicles can easily and quickly swap modules to meet contemporary mission requirements.

As indicated, the modularised concept is applicable to both trucks and trailers as shown by current day examples in Figure 1 and Figure 2. As seen in these figures, allied with the modularised vehicle fleet concept is the adoption in cargo carrying vehicles of load handling systems that are organic to trucks (known as integral load handling systems, ILHS) and allow loading/unloading of modules from trucks and trailers without the need for other material handling equipment.

Quite apart from the strategic significance and complexity of the fleet mix issue, it is this modularised concept that adds a novel dimension to the problem addressed in this paper. While previous analyses have addressed container movement for example, we are not aware of such a modularised concept being examined, and also note that the wide use of trailer assets in military fleets introduces a further range of issues that have received relatively narrow investigation in the literature.

The Modularised Fleet Mix Problem (FMFP) we examine in this paper therefore can be stated as:

> A deployed military force has a range of mobility tasks to be undertaken utilising a heterogeneous modularised vehicle fleet incorporating truck and/or trailer operations. The deployed military force along with its vehicle fleet is distributed among many locations in an area of operation. Each mobility task is characterised as requiring a number and range of modules to be moved between locations, to meet a priority for movement, within time window constraints. Each truck and trailer type has characteristics in terms of its ability to carry a particular range and number of modules and its ability to move across particular terrain classifications at particular speeds. The problem is to select trucks, trailers and modules assets so as to provide the best fleet outcomes. The fleet mix options are to be assessed against several efficiency and effectiveness criteria.

3. FLEET MIX PROBLEMS AND APPROACHES

Most of the fleet mix problems framed within the literature incorporate the determination of other fleet management problems, such as vehicle assignment, vehicle routing, and/or vehicle scheduling within a network of customers or demand locations. These problems are often referred to as, or founded upon, the classical Vehicle Routing Problem (VRP), Vehicle Scheduling Problem (VSP) and combinations or variants thereof. The survey by Bodin et al[2], despite its age, continues to be cited as one of the most comprehensive undertaken in this area of interest. Along with this survey, Desrochers et al[3] highlight the great variety of problem types examined in this domain and the principal characteristics that differentiate them.

As Fisher and Jaikumar[4] point out ‘literally person-centuries have been devoted to developing a sophisticated theory’ for problems in this domain. As such, resource routing, scheduling and assignment represent huge fields of research endeavour where the application of heuristics and meta-heuristics is prominent. Ruiz et al[5] also note that while solution approaches based on exact methods have been applied for reasonably sized problems, generally only basic versions of such problems, such as the VRP or VSP, are considered.

The fleet mix problem presented in this paper is most closely aligned with the VSP; being to complete a range of tasks, from multiple depots, employing appropriate assets with established time windows so as to optimise such aspects as the number of vehicles of various types, fixed and variable costs, and vehicle capacity utilisation. Some recent examination of the vehicle scheduling type problems can be found in Park[6] [7], Baita[8], Dell'Amico et al[9], and Ferland and Michelon[10]. In this area the literature demonstrates the application of a wide range of heuristic and meta-heuristic solution approaches.

However, despite this interest in vehicle operations, few applications of combined truck and trailer fleet mix problems are to be found in the literature. Those few areas of investigation are generally aligned with either the Vehicle Routing Problem with Trailers (VRPT), the Truck and Trailer Routing Problem (TTRP), or the Truck and Trailer Vehicle Routing Problem (TTVRP).

Semet and Taillard[11] consider a VRP that includes the use of trailers under accessibility constraints. Semet[12] similarly models a related problem called the 'partial accessibility constrained VRP'. As an extension of the VRP, Semet categorises customers as either 'trailer-customers' and therefore accessible by either a truck or a truck-trailer combination, or as 'truck-customers' and therefore accessible by a truck only.

Gerdessen[13] examines a similar extension of the classical VRP entitled the VRP with trailers (VRPT) to determine optimal truck and trailer combinations. This problem is based on the consideration that manoeuvring problems may be encountered at certain customer sites. As a result the problem considers unhitching trailers at various parking sites in order to visit some 'difficult' customers with an easily manoeuvrable truck only.

Chao[14] considers a related problem identified as the Truck and Trailer Routing Problem (TTRP). In this case the core of the problem is as presented by Gerdessen; however, a number of important assumptions are relaxed. The VRPT studied by Gerdessen differs from Chao's TTRP in that all customers have unit demand, customers are assigned manoeuvring times instead of customer types, each customer location can be used as a trailer parking place and each trailer is parked exactly once. In their heuristic solution approaches both Gerdessen and Chao develop construction and improvement algorithms. Chao, however, applies a solution construction method and a tabu search improvement heuristic together with the deviation concept found in deterministic annealing to solve the TTRP. In a later article Scheuerer[15] also considers the TTRP and proposes two construction heuristics for this problem and a tabu search heuristic.

The previously mentioned problem constructs involving trailer operations lay in the domain of vehicle routing. With the addition of time windows, Tan et al[16] introduce an element of scheduling when examining the Truck and Trailer Vehicle Routing Problem (TTVRP). In addition to time windows, unlike the TTRP, the TTVRP:

- requires vehicles to visit designated trailer exchange points for picking up the correct trailer types depending on the tasks to be undertaken,
- models trucks as essentially prime movers with no organic carrying capacity (i.e. trucks do not operate independently of trailers), and
- allows for the outsourcing of tasks that are not routed by sub-fleets in the TTVRP.

Tan et al propose a hybrid multi-objective evolutionary algorithm incorporating specialised genetic operators, variable length chromosome representation and a local search heuristic to find the Pareto optimal routing solution.

4. APPROACH

The problem we introduced in the introduction is more complex than what can be found in the literature, and consists of a number of coupled sub-problems. Before we discuss our approach, we will state the problem formally. In the discussion presented here, we will ignore the trailers.

Assume a command structure defined as a tree-graph $C = (U, O)$, where U are the units in the command structure and O is the set of edges representing which unit is in command of which unit. Each unit is split into a set of capability groups (sub-units). The command structure defines the ownership of vehicles, thus a vehicle owned by a unit is not allowed to be used by any other units. The command structure becomes important if we allow that a vehicle owned by a unit can be used by any other unit who is in command of the former unit.

Assume a nodal structure represented as a graph $G = (N, E)$, N is the set of nodes, while E is the set of edges. Each node is associated with a number of properties including the size of the node, the average length between any two points within the node, the maximum day and night speed of internal roads and the unique set of capability groups located at this node. Each edge has a number of parameters associated with it, including the mobility criterion of the road, the length, width, and maximum load (for example, when there is a bridge, the load is limited), and maximum day and night speed of vehicles travelling on the road.

Assume the existence of V^k vehicles, where k represents the combination of modules that the vehicle can carry. Assume the existence of M^r modules, where r is the set of materials that can go with each module. Assume the existence of T_d^w tasks, where w is the time window in which a task needs to be fulfilled, and d as the duration of the task. The problem is to identify a mixture of vehicles and modules to fulfil the tasks such that (1) the cost is minimum; (2) the mixture is balanced (a balance between different vehicle types and module types); (3) the lane meter (a measure that describes the space a vehicle occupies in a strategic sealift vessel) is minimum. Typically, the three objectives exist in conflict, i.e. fleet options that are optimal when assessed against one of the objectives do not optimise the other two objectives. The mixture balance is calculated through the entropy of the fleet mix vector.

The amount of materials that can be loaded on a module is constrained by the module payload in volume, payload in kilograms (kg), and the combination of materials that can be carried by this module. A vehicle is also constrained by the different combination of modules it can carry, the availability of a driver with the right skill set to operate the vehicle, and the mobility criterion of the vehicle which restricts its ability to move on certain terrains. In addition, the vehicle can only be assigned to a task owned by the owner of the vehicle. Types of vehicles or modules have different characteristics such as payload, fuel capacity, driver skill level, dimension, crew required, maintenance parameters, and purchasing price.

Tasks are characterised through a set of materials described in terms of type, quantity, and volume, an early start time and date, a latest finish time and date, a duration, a priority, a source or origin of the task, a destination, and a set of intermediate deliver nodes if needed with their own local demand, frequency for doing the task, preferred vehicle if known, and preferred module if known.

We assume that the vehicle will return to the origin after fulfilling the task. A working day is eight hours for a driver. The daylight period is from 6am to 6pm and the night time is the rest of the day. We assume a fixed loading and unloading time for the vehicle.

When solving this problem, time is the essence. Given that the size of operation imposes a huge number of tasks, it is not convenient to allow the solver to generate many (sometimes any) infeasible solution. Thus, we designed the solver around the concept of generate-mix-improve. Before explaining this concept, it is important to discuss a number of pre-processing subroutines. These subroutines are inefficient when the problem size is small as they have a large fixed-cost. However, when the problem size becomes large, these subroutines save a huge amount of time.

The first subroutine is the routes subroutine. This subroutine is responsible for generating all possible routes between any two nodes in the network. This is an exponential list. However, given that the network we are dealing with tends to have a small average degree per node, the complexity of these subroutines is not that expensive. Once these routes have been generated, a number of measures are calculated for each of these routes. These measures are mobility criterion (the worst mobility criterion of the route), the total distance of the route, and the maximum load that can be transported through this route.

The second subroutine is the combination subroutine. This subroutine enumerates the possible list of modules that can be carried with each vehicle type. For each combination, the total payload in kilograms and volume, and the mobility criterion of the vehicle are calculated.

The current solver is designed as presented in Figure 3. The system is characterised by a unique and modular structure which provides the system with the required flexibility to evolve over time with minimal changes. The engine consists of three main components: (1) the schedule manager; (2) the task manager; and (3) the vehicle manager. The schedule manager coordinates the synchronisation between the task manager and the vehicle manager. It provides the main internal interface for exchanging data and information between the other two components as well as the recombination operation of Stage 3 of the heuristic presented below.

The scheduling heuristic is divided into three stages. In the first stage, a single feasible solution is generated according to some heuristic. In the second stage, the first stage is called a number of times to create a number of feasible solutions. In the third stage, the solutions are combined and new solutions evolve.

We will focus first on Stage 1. The Task Manager is responsible for choosing a task for the schedule manager to schedule. When a task is selected for scheduling, the Task Manager orders the task using a random sequence of the following set of criteria:

- Descending order on earliest start time
- Descending order on latest finish time
- Sorting the origins according to names
- Sorting the destination according to names
- Sorting on priority from important to less important with 1 being the highest priority
- Descending or Ascending order on weight
- Descending or Ascending order on volume

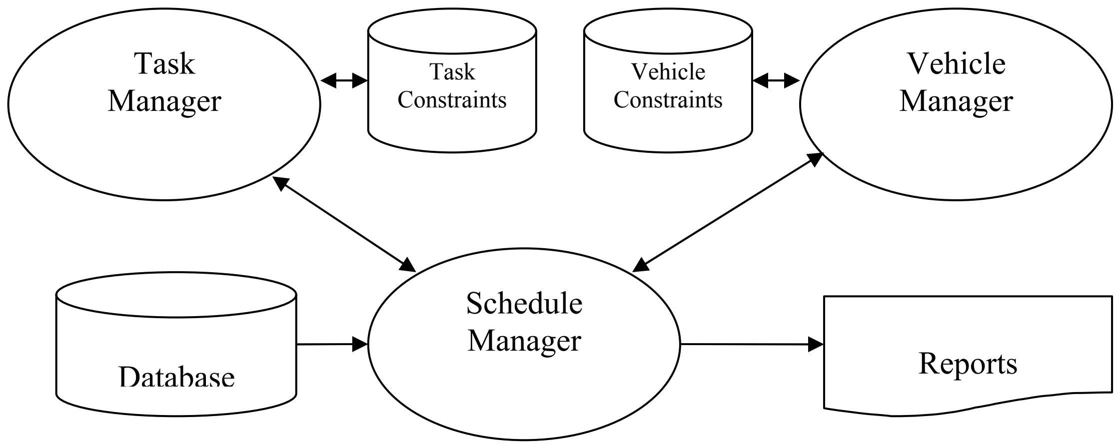

Figure 3. Modular Structure of the Solver System

Once the Task Manager has sorted the tasks, a task is selected and its characteristics are passed on (by the Schedule Manager) to the vehicle manager so that the Vehicle Manager can select a suitable vehicle for the task. If there is no suitable vehicle available to perform a task, then the Vehicle Manager has access to an (unlimited) pool of vehicles in order to "create" the required vehicle. The vehicle selection process uses the following constraints:

(1) The default start time for a task is 6am.

(2) A driver (also a vehicle) cannot operate more than ten hours a day.

(3) Every five hours, the driver/vehicle must task a break for 30 minutes.

(4) If the sum of the duration of the trip and the time the vehicle has been operating so far without a break is greater than the maximum allowed time to operate without a break, the driver will take a break before commencing the task

(5) The mobility criterion of a vehicle needs to be suited to the road. Here we assume that a vehicle with a mobility criterion VM can be used for a road with mobility criterion RM if VM ≤ RM.

(6) The class of supply for the vehicle is consistent with the materials to be transported. The heuristic is configured to prefer a light vehicle over a water tanker if the amount of water to be transported is less than 1000lt.

(7) If the vehicle is an existing one (it has been created before), the owner of the vehicle must reside at the location from where the task originates.

(8) Volume, pax, and weight of task must be less than those of the vehicles.

The main algorithm is given below

```
Stage 1:
        Initialize SList to empty
        For each task T in the sorted task list
                Until T is completed (T.quantity>0)
                        While there is combination available based on T
                                Obtain one combination C
                                while there is a route available based on T and C
                                        Obtain one route R
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                                    while there is a set of modules based on T,C,R
                                            Obtain this set of modules M
                                            Break;
                                            While there is a vehicle based on T,C,R
                                                    Obtain vehicle V
                                                    Reset the available time of V and M
                                                    Break;
                                            End While
                                    End While
                            End While
                    End While
            End Until
    End For
    Add the schedule to SList
Stage 2:
    While (time-elapsed < time-available)
            Shuffle the orders for sorting
            Call Stage 1
    End while
Stage 3:
    While (time-elapsed < time-available)
            Select 2 schedules S1 and S2 from SList
            Let S3 = Operator(S1,S2)
            If Size(SList < Maxmimum size allowed)
                    Add S3 to SList
            Else
                    Apply replacement strategy
            End if
    End while
```

The *operator* in Stage 3 is a recombination operator which takes two schedules, and exchanges some aspects about each of them to generate a new schedule. We will not discuss this operator in detail in this paper.

5. CASE STUDY

In this section, we present two simple examples to demonstrate the functionality of the system. Both examples share the same characteristics except for the cost function associated with the purchase price of the vehicles. In each example, we will have two nodes connected by a 240 kilometres (km) long road. There are three vehicle types: heavy (mobility criterion 3, day speed 60 km/hour, night speed 40 km/hour), medium (mobility criterion 2, day speed 80 km/hour, night speed 50 km/hour) and light (mobility criterion 1, day speed 80 km/hour, night speed 50 km/hour). There are also three different module types which can carry up to 1000, 500 and 100 kg of materials. There are two materials that can move together, food and ammunition. The early start time for all tasks is the start of the day and the latest finish time is eight hours afterwards. All tasks start from Base 1 and need to be delivered to Base 2. There are ten tasks on Day 1 of 100 kg each, five tasks on Day 2 with 500 kg each, and three tasks on Day 3 with 1000 kg each. The cost function in Example 1 is 1800 (arbitrary units) for heavy, 950 for medium and 200 for light vehicles. The cost function in Example 2 is 2000 for heavy, 1400 for medium and 400 for light vehicles. The slope of both functions (purchase price divided by the vehicle capacity in kg) is shown in Figure 4.

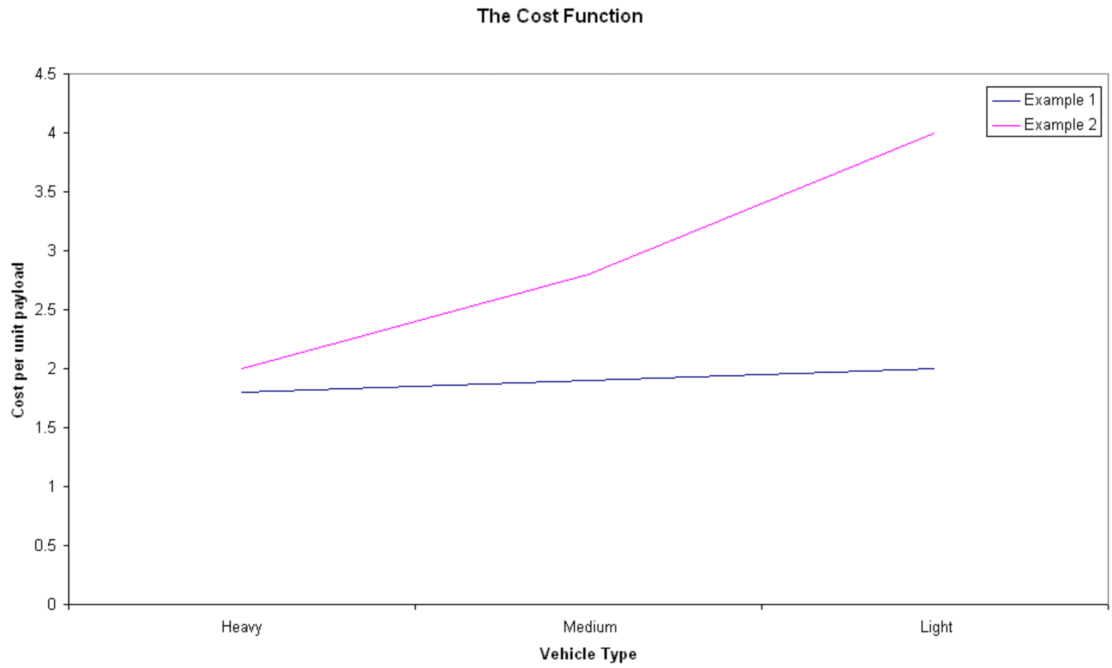

Figure 4. Cost function for the truck types in the two examples described in the text

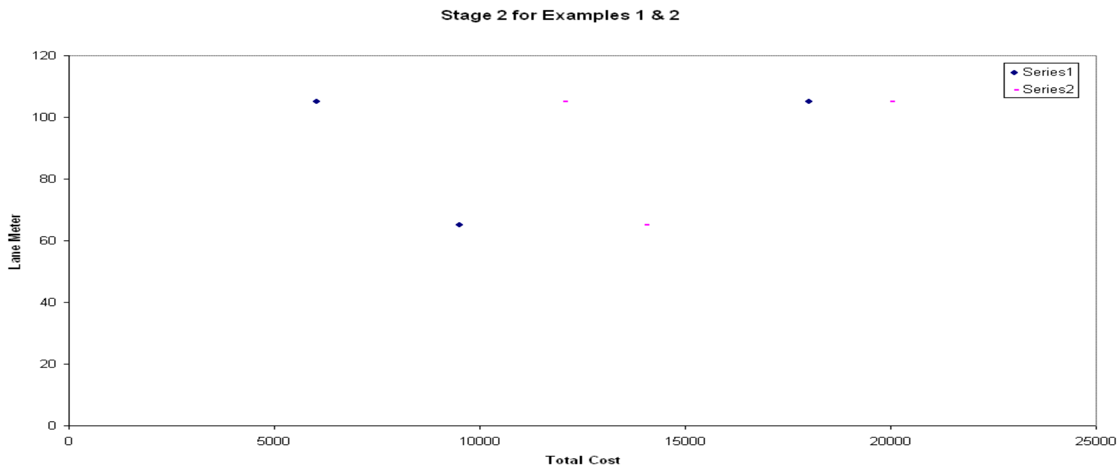

Figure 5. Outcome of running stage 2 in the two examples of the case study

Figure 5 shows the outcome of Stage 2 of the solver system. As can be seen, there are three different solutions in each example. These solutions represent extreme cases because of the bias associated with fixing the way the criteria are sorted.

In Stage 3, however, optimisation starts by combining the solutions generated in Stage 2. Figure 6 shows the outcome of Stage 3 for both examples. It is interesting to see the effect of the cost function on the distribution of the generated solutions. More specifically, if we draw a line to separate each pattern into two halves, we see that the algorithm undertakes more uniform exploration on both sides of the line when the slope of the cost function is high.

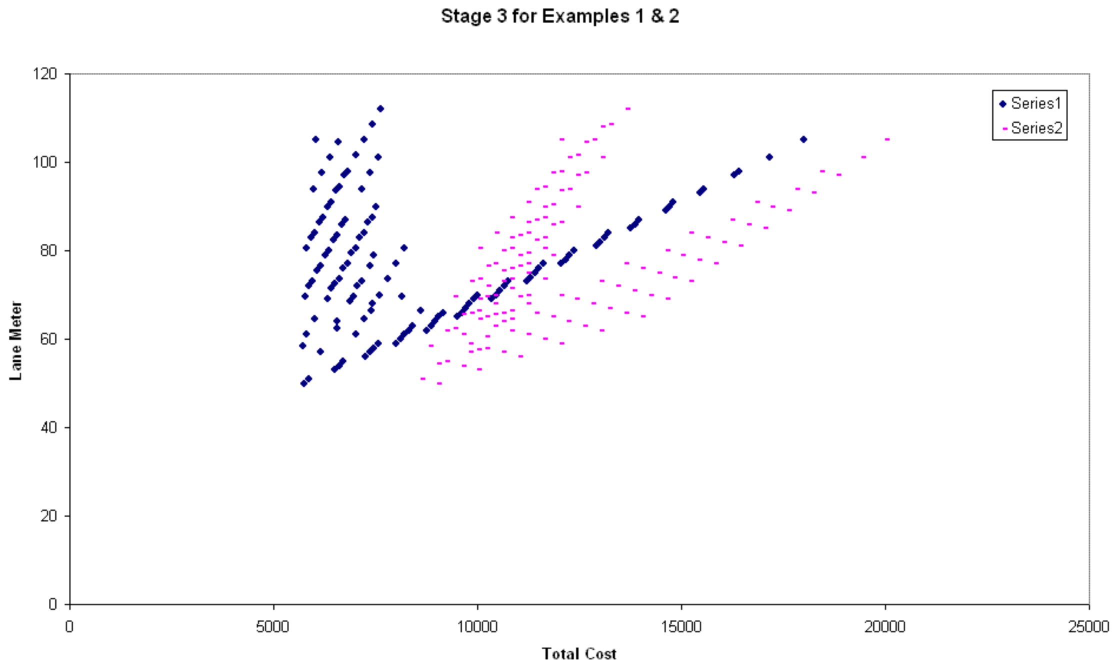

Figure 6. Outcome of running stage 3 in the two examples of the case study

6. CONCLUSION

Applying the presented solver system to the simple case study illustrates that (1) schedule recombination (Stage 3) results in improvement in the fleet mix solutions found in Stage 2, and (2) the solver system produces fleet options with great efficiency at low computational cost. This instils confidence that the developed method can be applied to more realistic, and thus more complex, examples.

However, examining examples is not equivalent to proofing the effectiveness of the approach. We are currently working on refinements to the heuristics employed in the three stages of the solver system, and the definition of optimisation objectives that provide a “good” spread for the Stage 2 seed solutions upon which improved solutions are generated during Stage 3. We have also started to investigate the structure of the fleet option landscape in order to obtain a better understanding of the accuracy of the optimisation approximation used, and to evaluate computational effort required to find accurate approximation. In future work, we will continue with the development of the solver system to enable the optimisation of vehicle fleets that operate in dynamically changing military environments characterised, in parts, by enemy disruption and high uncertainty of demands in supply classes, such as ammunition.

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