2009

Human-Assisted Logistics Optimization (HALO): Support for Timely Logistics Decision-Making

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HUMAN-ASSISTED LOGISTICS OPTIMIZATION (HALO):
SUPPORT FOR TIMELY LOGISTICS DECISION-MAKING

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The need for rapid response capabilities and effective joint operations dictates a new approach in which deployment planning is integrated into the mission-planning processes. In the research reported here, we explored new technologies to enable rapid identification of feasible transportation options and enhance shared awareness of commander's intent and inter-command collaboration. Our solution extends state-of-the-art Tabu Search algorithms, producing effective transportation solutions in significantly less time than current models. The human guidance and collaborative components of HALO enhance performance by accommodating dynamic operational requirements. HALO benchmark tests demonstrated superiority to other optimization algorithms on Multi-Vehicle, Pickup and Delivery Problems with Time Windows (MVPDPTW) reported in the literature. When applied to intra-theater MVPDPTW distribution problems, HALO generated feasible, near-optimal solutions acceptable to subject matter experts in less than a minute. We conclude that HALO is a powerful decision tool that is easily integrated into current planning processes with strong user acceptance.

Logistics support, including force deployment and sustainment planning and execution, has traditionally been viewed as a support function to combatant commanders, even though it is one of the key enablers (and limiters) of any military operation. In this model, up-front mission planning and course of action determination is accomplished in a somewhat stovepiped fashion, with relatively little visibility into transportation constraints. These initial requirements are then handed off to Logistics planners to define transportation options that can best support the combatant commander's needs. Through an iterative and cooperative process involving both the supported command (e.g. United States Central Command - USCENTCOM) and the supporting commands (e.g. United States Transportation Command -USTRANSCOM), transportation options are identified, analyzed, and validated. The initial operational plan often needs to be adjusted based on time-phased deployment constraints or shortfalls identified during the transportation option analysis and selection process.

The changing nature of the threat and the associated need for greater mobility, flexibility, efficiency, rapid response capabilities and effective joint operations dictate a new approach. With the recent rapid growth in information and communication technologies, military operations are transforming into a network-centric model that emphasizes shared situation awareness, visibility of a common operating picture and commander's intent, and self-synchronization of distributed forces. This model enables unprecedented levels of collaboration, faster decision-action cycles, and the flexibility to adapt quickly and effectively to changing requirements, priorities and situations. Realization of this model requires that force deployment planning become an integral component of the core mission planning process so that logistics considerations, the opportunities afforded, and the constraints imposed, are known and accounted for in real time during the planning of combat operations.

Thus, our overall goal was to research requirements and design concepts for a Human-guided Tabu Search algorithm that generates an optimal Airlift transportation solution for satisfying operational requirements. To achieve this goal we researched approaches for (1) improving speed of solution convergence, (2) incorporating commander's intent, (3) improving collaboration among operational and logistics planners, and (4) adapting to dynamic preferences and priorities. Based on this research we developed proof-of-concept demonstration software to test hypotheses and verify the efficacy of our approach. We named our demonstration software "Human Assisted Logistics Optimization," or HALO.

Background and Theoretical Approach

Group-Theoretic Tabu Search (GTTS) in Logistics Planning

McKinzie (2004, p. 2) describes the movement of cargo and passengers (PAX) within certain time-window constraints as a highly complex routing and scheduling problem called the Strategic Mobility Mode Selection Problem (SMMSP). The literature characterizes SMMSP as a variant of the Multi-Vehicle Pickup and Delivery

Problem with Time Windows (MVPDPTW), which is a complex generalization of the "Traveling Salesman Problem" (TSP) - a well-known and heavily-studied nondeterministic, polynomial-time, hard (NP-hard) problem (McKinzie, 2004, p.22).

Many types of metaheuristics are applicable to MVPDPTWs as well as other types of logistics and scheduling problems: ant algorithms, Bayesian algorithms, constraint programming, deterministic annealing, genetic algorithms, greedy algorithms, memetic algorithms, multi-objective evolutionary algorithms, simulated annealing, and Tabu Search. Of the numerous deterministic and heuristic search algorithms applied to MVPDPTWs, Tabu Search has proven the most effective (Crino, et al., 2004; Lambert, 2003; McKinzie, 2004). Basic Tabu Search (Glover, 1989, 1990) is a metaheuristic algorithm for solving optimization problems. It is designed to guide other deterministic or heuristic methods so they can escape local minima and prevent oscillations between previously tried solutions; thereby enhancing the likelihood that a global minimum to a "cost function" will be found. A basic Tabu Search algorithm consists of the following:

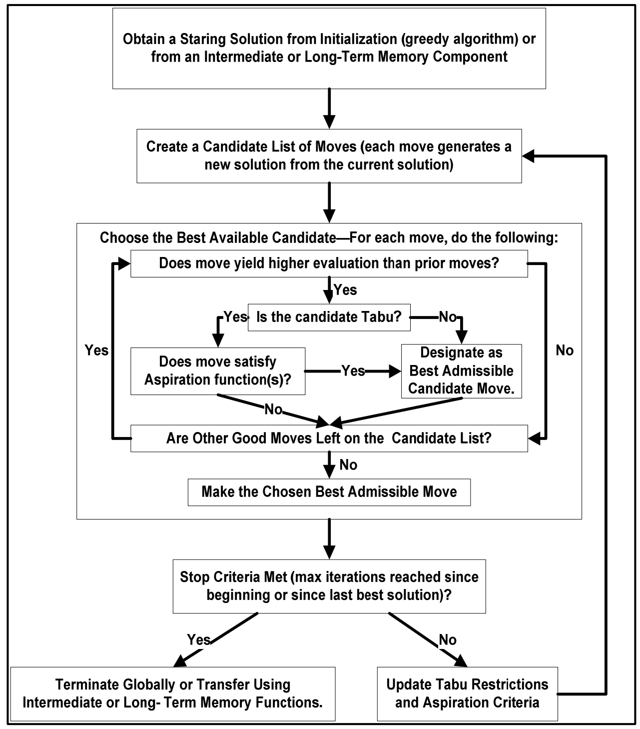

Figure 1. Basic Tabu Search Algorithm.

- A representation of the problem space being searched. In the TSP this would be a matrix representation of the graph consisting of the cities (vertices) and highways or air routes connecting the cities (arcs).

- A short list of previously tried "moves" that are TABU; that is, as long as a move is on this list, it (or its reversal) cannot be tried again. The Tabu list is designed to keep the algorithm from cycling around a local minimum and to encourage breaking out of the local minimum. The length of the list determines how long a move is "Tabu." If there are a number of constraints that apply to the problem, a separate Tabu list may be kept for each constraint.

- Zero or more *aspiration level functions (alfs)*. The purpose of an *alf* is to provide added flexibility to choose good moves by allowing the Tabu status of a move to be overridden (removed early from the list) if the *alf* is satisfied. The form of an *alf* depends heavily on the search problem and includes the cost of the move (however "cost" is defined in the problem).

- Zero or more intermediate and long-term memory functions. These may be added to the basic Tabu Search algorithm to achieve regional intensification of the search or global diversification of the search. By recording and comparing features of a number of "best" solutions reached during a given period of search features common to all, or a majority, of these solutions are used to guide the search by penalizing moves that do not contain these features—resulting in regional intensification. The long-term memory functions serve to diversify the search by deliberately avoiding moves (and solutions) that have common features as defined above.

- The Tabu Search algorithm itself. Figure 1 shows the logical flow of the basic Tabu Search algorithm including all components listed above.

Group Theoretic Tabu Search (GTTS) applies algebraic group theory to the representation of MVPDPTWs. In this approach, vertices and arcs in the MVPDPTW graphic representation are mapped one-to-one onto the finite set A consisting of {1, 2, 3, … , n}, and the symmetric group of n-letters, S_n, is the group of all permutations of set A. This allows the representation of arbitrarily large MVPDPTWs as a 2 x n matrix or array with the first row containing the numbers 1 through n and representing the vehicles and customers[1] in the MVPDPTW. The elements of the second row in its most elegant form contain "cycles" of pickup, transport, delivery, and return—represented by the numbers from row 1 in a short list. (See Crino, et al., 2004, for a detailed and precise description). In this representation a move is a swap of elements within or between cycles, or adding or dropping an element in a cycle. This approach was applied to a large combat theater distribution vehicle routing and scheduling problem (a member of the class of MVPDPTW) with significant success. The best solution was found in just under 63 minutes; however, two near optimal solutions were found after only 11.5 and 24.5 minutes. The use of algebraic group theory in the representation of a given MVPDPTW is a major innovation: elegant in its simplicity yet enormously powerful in its effect, both in solution speed and achievement of near optimal solutions early in the search.

Transportation Optimization as a Joint Cognitive System (JCS)

The role of decision support technology should be to serve the humans who are ultimately responsible for the decision. A JCS is a system in which the human and machine work collaboratively to solve a problem or make a decision (Woods & Hallnagel, 2006). The software component is a cognitive tool that can be wielded by a competent practitioner. This approach exploits the complementary knowledge and "reasoning" processes of the human and software components to obtain better decisions than could be achieved with either alone. In a JCS, the human serves as a manager of knowledge resources that can vary in kind and amount of "intelligence" or power. A JCS is an alternative architecture to the traditional approach of applying computational technology as a stand-alone machine expert that serves as a replacement for perceived human deficiencies; i.e., the "prosthetic" paradigm (Woods & Hallnagel, 2006). JCS architectures avoid many of the problems introduced by the prosthetic design approach (Guerlain, 1999). Problems outside the machine's level of competence no longer lead the human to ineffective solutions. Instead, those aspects of the problem that the machine expert does know about are used effectively to aid in the overall solution. Issues related to trust, complacency, over-reliance, control, and responsibility are decreased.

The JCS approach drove the development of HALO. We inserted the user into the heart of the GTTS algorithm. Users can manually modify candidate solutions, backtrack to previous solutions, modify the tabu list, *alfs*, and any other cost parameters associated with problem elements, and monitor or halt the search algorithm. The User Interface provides an operationally meaningful visualization of the current and other potential search solutions, some intuitive indication of the progress and current attentional focus of the algorithm within the search space, and controls for manipulating and guiding the search algorithm. To be "operationally meaningful" the visualization must represent information and candidate transportation solutions in terms of the operational constituents of the problem set, such as Ports of Debarkation, Ports of Embarkation, waypoints and routes, aircraft assets, cargo, timing profiles, etc. Users must be able to manipulate these objects graphically to obtain detailed information and manage how they are considered within the algorithm. We developed our human guidance component by drawing on recent work in human-guided Tabu Search (e.g. Lesh, et al., 2003; Anderson, et al., 2000) and integrating the JCS approach described above. With respect to the strategic mobility optimization problem and the deployment planning process, the human guided component provided a means of ensuring that commander's intent and practical knowledge of real-world constraints were considered in the optimized transportation solution.

Research Procedures

HALO development process. The following procedural steps were carried out to assess the efficacy of HALO: (1) We acquired existing open source Tabu Search software (OpenTS) and modified and integrated it with human-guidance control functions that would allow users to guide the search by setting and modifying search parameters.[2] (2) We acquired the necessary GTTS objects and methods from the code written by Burks (2006) and integrated them with the OpenTS software. (3) We identified optimization strategies that could be incorporated into the code, implemented them in additional objects and methods, and exposed them to the user interface to put the

[1] Vehicles are the air and ground transports used to move cargo and PAX. Customers are the origins, Ports of Debarkation, Ports of Embarkation, service and destination hubs, and delivery points.

[2] OpenTS can be downloaded from the web site: http://www.coin-or.org/Ots/index.html.

search under human control and guidance. (4) We created a specific Theater Distribution Problem (TDP) scenario to test our hypotheses and refine the JCS architecture. And, finally, (5) we tested HALO using variations of the TDP and compared the results to benchmark solutions for the TDP using Basic Tabu Search and GTTS. We also demonstrated HALO to logistics experts to obtain feedback on the utility and usability of the tool.

TDP scenario description. The selected scenario was a hypothetical, high-intensity, small-scale contingency operation with a highly compartmentalized Area of Operations (AO). There were two stages of operation: deployment and sustainment. The planning goal was to determine the support structure and routing requirements necessary to (1) deploy forces from staging bases in Turkey to Tbilisi, Georgia and Yerevan, Armenia and (2) to sustain combat operations in the AO. We created several variations on the scenario to allow testing and benchmark comparisons. This also allowed us to demonstrate the capabilities of HALO to Subject Matter Experts.

JCS user interface. This interface allows the user to control critical functions in the execution of HALO software while displaying the results of the search in a multi-document display. The GTTS functions under control of the user include (1) starting, stopping, resetting the search, (2) adjusting the impact of thirteen components of the GTTS "cost" function before and during execution of the search, (3) set problem parameters such as the number of planning days, whether vehicles are allowed to refuel enroute, crew work hours, and whether vehicles are allowed to arrive early at a depot, service or destination hub, or a delivery point, and (4) save solutions, reload solutions, and resume solution searches. The user interface display is shown in Figure 2 with the four main windows open for inspection. The four main windows provide the following displays and functions:

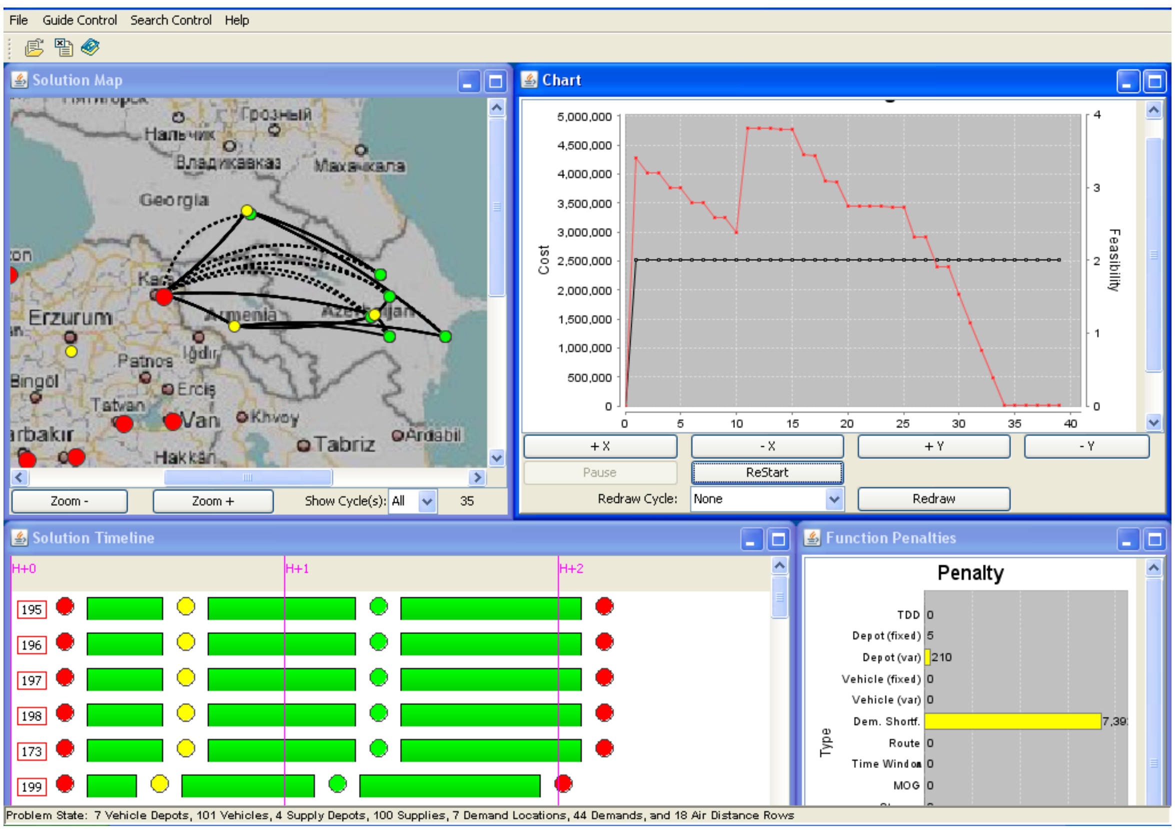

Figure 2. JCS user interface for HALO.

- Map Display Window (upper left quadrant). Displays a map of the Theater of Operations with vehicle depot, supply depot, and demand locations shown by color-coded symbols (red, yellow, and green circles, respectively). As routes are built and removed by the Tabu Server on each iteration, the route changes are displayed in this window.

- Route Timeline Window (lower left quadrant). Displays each vehicle route in the form of a timeline for easy detection of various route violations. This is the main window for examining vehicle and route properties. Users may “mouse-over” a route symbol to see a brief description of the entity represented by the symbol, or “right-click” to get a full description of the selected route and vehicle properties.

- Cost/Feasibility Chart Window (upper right quadrant). Displays changes in the Objective Cost Function and Feasibility of the solution found on each iteration of GTTS. The display is in near-real time. Figure 2 shows the state of the search on the 39th iteration of the search. The search has been paused temporarily to examine in detail the solution found on the 34th iteration. The solution at this iteration is near-feasible (value = 2) and has an Objective Cost of 10,247. The Map Display Window and Route Timeline Window now display their states at the 34th iteration.

- Cost Breakdown Bar Chart Window (lower right quadrant). Displays the individual components of the Objective Cost Function. This bar chart gives immediate visual understanding of the penalty costs that are the cause of the “near-feasible” classification of the solution produced on the 34th iteration. The largest “cost” is Demand Shortfall followed by Time Definite Delivery violations and the Depot cost (these are the largest penalties because the weighted parameters in the cost function have been set to focus on timely delivery of the cargo and PAX. Users may right-click on a bar to see a detailed breakdown of the objects contributing to the objective cost or penalty cost represented.

Figure 3. HALO cost function dialog box.

GTTS cost function control. HALO provides access to the GTTS cost function weights through a dialog box accessible from the “Guidance Control” menu. The HALO default weight settings for the thirteen components of the GTTS cost function are shown in Figure 3 and support a general intent of “minimizing the logistics footprint” in support planning. The first six components are “costs” associated with vehicle depot, supply depot, and vehicle fixed and variable costs (variable costs are associated with vehicle and depot maintenance and ongoing operations). For a military operation requiring tight time windows and no demand shortfalls where the commander’s intent is absolute assurance that the warfighter receives supplies when needed (as in the benchmark TDP contingency operation described above), the depot and vehicle cost weights would be minimized and the weights for Time Definite Delivery, Demand Shortfall Penalty, Route Length Violation Penalty, Depot Queue Violation Penalty, and Time Window Violation Penalty would be maximized. If commander’s intent is something other than these two scenarios, the thirteen weights would be adjusted to reflect that intent.

Benchmark Results and Conclusions

Tests on HALO were limited to TDPs, which tend to be of shorter duration requiring fewer resources. Nevertheless, we were able to use test data supplied by Burks (2006) as well as several variations on our scenario to obtain both benchmark and scalability results. Tests on these data yielded the following computational-time results: (1) For small TDP scenarios (150-200 nodes), multiple optimum solutions with lowest cost were produced in less than 40 seconds. The initial optimal and feasible solution often appeared in the first 10-20 seconds. And (2) For intermediate TDP scenarios (200-600 nodes), optimum solutions with lowest cost were completed in less than three minutes and low cost, near-optimum solutions were available as early as 45 seconds into the search. This performance exceeded basic Tabu Search (e.g., Tan, et al., 2000) and GTTS without human guidance (Burks, 2006). It also easily surpassed non-Tabu search (genetic) algorithms (e.g., Homberger and Gehring, 2005).

In conclusion, the HALO software architecture represents an optimal approach to collaborative logistics planning and it appears to be fully scalable, although further research is needed to establish firmly its utility in supporting Strategic Airlift Problems and Strategic Mobility Mode Selection Problems. Also, we conclude that human-guidance controls strongly support a JCS architecture for logistics planning. Proper use of these controls can dramatically shorten search time and produce optimal solutions that accurately reflect commander's intent. Finally, we conclude that a JCS contributes significantly to user acceptance and positive regard for the HALO software.

Acknowledgements

This research was supported by a Phase I Small Business Innovation Research grant from the Air Force Research Laboratory under contract number FA8750-07-C-0122. The views, opinions, and/or findings contained herein are those of the author and should not be construed as an official Air Force position, policy, or decision. The author also thanks Scott M. Cone, James T. Moore, and Robert E. Burks for their contributions to this research.

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