Air Movement Operations Planning Heuristic Improvement

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Abstract

Purpose - Improve the air movement operations planning heuristic in the literature to generate better solutions in a shorter time period.

Design/Methodology/Approach - Through a rigorous design of experiments, we make significant heuristic improvements by evaluating alternative modular methodologies and tuning heuristic parameters for two scenarios. This includes a new approach to considering refueling operations.

Findings - We find the fine-tuned heuristic averages a 33% objective improvement and 70% reduction in computation time over the heuristic with original parameters for one of the scenarios. Additionally, we analyze the heuristic's quality of solution over time.

Research limitations/implications - Further analysis is required to generalize heuristic settings, which would require significant access to operational data or a portfolio of scenarios of interest.

Originality/value - This research provides novel vehicle assignment and routing heuristic improvement alternatives and demonstrates a design of experiments-based heuristic tuning procedure.

Practical implications - Tuned heuristic parameters reduce the computation time from hours to minutes. This also makes it practically feasible to adjust parameters in the objective function to generate multiple courses of action for a given instance.

Keywords: design of experiments, heuristic improvement, dial-a-ride problem, multiple refuel nodes, demand priority, helicopter routing, aircraft, military aviation

1 Background

US Army units solicit helicopter support from Army Aviation units using an Air Mission Request (AMR) process (Department of the Army [DA] 2020*a*) to support air movement operations which move personnel, supplies, and equipment throughout an area of operations (Department of the Army [DA] 2020*b*). The unit requesting support routes the AMR through their chain of command where higher echelons conduct quality control and consolidates the requests for onward submittal to the next echelon. At the brigade level, the brigade aviation element (BAE) provides aviation subject matter expertise for filtering and prioritizing the AMRs to best employ helicopter assets. The BAE submits the final AMRs to the next headquarters, usually a division. The division tasks the AMRs to the aviation unit for execution. Standard processing times from the BAE's receipt of the tasking to the planned air movement is 96 hours, though dynamic requirements often involve requests submitted within 24 hours of the desired movement.

The aviation unit tasks the AMRs to the appropriate subordinate aviation battalions and/or task forces based on mission type, required equipment, aircraft needed, and other factors. These aviation battalions must task each AMR to an aircraft team and generate routes for the aircraft team to complete all assigned AMRs and associated requirements. No later than 12 hours prior to the desired time of air movement, the aviation unit publishes a daily air movement table to convey the results of the planning process back to the unit requesting aviation support.

Aviation mission planners have 12 hours (although often less) to task and route aircraft teams to support the AMRs based on AMR priority levels, locations, number of personnel, and pickup/dropoff time windows. According to a current general support avaition battalion commander, the current process can take a team of planners over five hours to generate a plan for a single day (Espinoza 2022). Nelson et al. (2023) introduce two models to task air mission requests (AMRs) to rotary wing aircraft teams and generate the required routes in order to minimize unsupported AMRs by priority level, number of helicopter teams used by utilization penalty, and total flight hours. A mixed integer linear program (MILP) is developed which generates optimal solutions but proves intractable for application-sized instances with 30–100 AMRs. A heuristic approach is developed which generates feasible solutions within a tactically useful time, but the authors note future work to potentially improve the heuristic. In this paper we investigate methodologies to improve the aviation air movement operations planning heuristic in order to generate superior solutions in less time. We make improvements by incorporating several alternative modular methodologies and optimizing heuristic parameters. The findings result from data collected during a rigorous design of experiments (DOE). This paper demonstrates its value in its final presentation of solution quality and time for various application-sized problems and compares the performance to Nelson et al. (2023).

2 Literature Review

The MILP model in Nelson et al. (2023) solves the US Army aviation air movement operations planning problem (Nelson et al. 2022) by formulating it as a dial-a-ride problem (DARP). The paper's research draws heavily on DARP research from Cordeau & Laporte (2007), Ho et al. (2018), and Nasri et al. (2021). The MILP includes additional features such as capacitated helicopter routing and multi-node refueling (de Alvarenga Rosa et al. 2016, Sundar & Rathinam 2012, Sundar et al. 2016). The air movement operations planning heuristic is an adaptation of the insertion algorithm for the single vehicle DARP (Häme 2011) into a multi-helicopter team heuristic to find quality feasible solutions to the problem.

The purpose of this research is to improve the air movement operations planning heuristic solution quality and computation time. In this paper, we demonstrate improvement through parameter tuning. Research in parameter tuning involves numerous methods, including teacher-learner optimizing algorithms (Rao & Kalyankar 2013, Yang et al. 2018), robust observer approaches (Beelen et al. 2020), and data analysis parameter approximation techniques (Wang et al. 2020).

Similar to this paper's methodology, there is ample research using DOE to tune model parameters. Lujan-Moreno et al. (2018) use DOE to screen the most important machine learning hyperparameters followed by a response surface methodology to fine-tune the hyperparameters. Similarly, Shankar et al. (2022) use DOE and response surface design to ascertain the key synthesis parameters and develop synthesized O-doped boron nitride models. O'Connor & English (2021) demonstrate a systematic factorial-design DOE to estimate optimal parameters of empirical water models. We use a methodology adapted from Gunawan et al. (2011) in creating a DOE approach to fine-tune algorithm parameters.

3 Fixed Time Heuristic Concept

Nelson et al. (2023) employ a heuristic that terminates when no improvement is made to the objective in subsequent improvement cycles, which then returns the best solution found. To compare performance for varying heuristic settings, Figure 1 presents the heuristic modified to run for a fixed amount of time.

Similar to the heuristic in Nelson et al. (2023), the fixed time heuristic starts with loading model inputs and determining which helicopter teams can support each AMR through the AMR assignment filter. The set of individually feasible AMRs per aircraft team is then sent to the initial AMR assignment module where it generates a set number of random assignments. In the original heuristic, the initial AMR assignment module randomly assigns AMRs to any helicopter team in the feasible AMR set. In this paper, we introduce a parameter to control the percentage of initial assignments that allow for unsupported AMRs or assignments to high-cost helicopter teams. High-cost aircraft teams are defined by the user when evaluating each aircraft team's utilization penalty, β. This parameter is further discussed in Section 4.2. The set of initial assignments

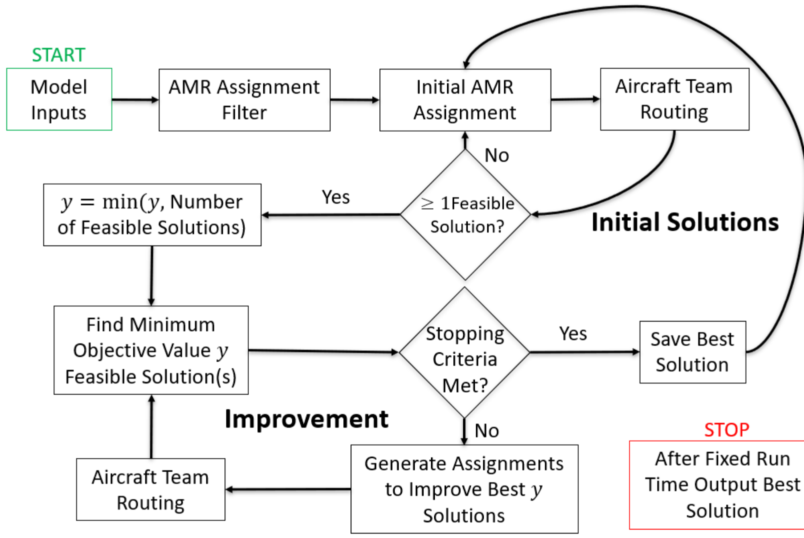

Figure 1: Fixed Time Heuristic Concept.
Conceptualization by authors.

then goes through the aircraft team routing algorithm adapted from the single vehicle DARP adaptive insertion algorithm (Häme 2011). This paper introduces an additional aircraft team routing algorithm that has the capability of inserting refueling stops at helicopter landing zones (HLZs) that do not have an associated AMR pickup or drop-off. Section 4.3 goes into further detail regarding the differences in the two aircraft team routing algorithms considered. Additionally, Section 4.4 evaluates the performance of the feasible route limit objectives described in Nelson et al. (2023).

For each initial assignment, the aircraft team routing algorithm outputs either a feasible routing for each aircraft team or determines that the AMR assignment is infeasible. If there are no feasible assignments, the heuristic returns to the initial AMR assignment module and generates a new set of random assignments. If there is at least one assignment with a feasible routing solution, the heuristic then sets the number of feasible solutions y to the minimum of the initial y value and the number of assignments with feasible routing solutions.

During the first improvement cycle, the stopping criteria are met if the assignment and routing solution with the lowest objective value supports all AMRs and the high-cost aircraft teams are not utilized. If the stopping criteria are not met during the first improvement cycle, the heuristic attempts to improve y assignments by redistributing unsupported AMRs to aircraft teams. The aircraft team routing module attempts to generate feasible routes for the improved assignments. The improved assignments with feasible routes are evaluated to determine objective values. Upon completion of the first improvement cycle, the stopping criteria are met when the lowest objective value of the improved assignments is the same as seen in the previous improvement cycle. For the fixed time heuristic, once the stopping criteria are met, the best solution is saved and the heuristic returns to the initial AMR assignment module. Upon every full iteration of the heuristic, the lowest objective value solution is maintained. As the predetermined computation time elapses, the heuristic outputs the solution with the lowest objective value. This solution consists of AMR assignments and aircraft team routing that meets all feasibility constraints from Nelson et al. (2023).

4 Heuristic Parameters

The purpose of this paper is to improve the air movement operations planning heuristic by tuning heuristic parameters in order to produce the solutions with the lowest objective values. There are six heuristic parameters that are considered. In order of heuristic execution, the heuristic parameters are as follows: initial AMR assignment quantity, unrestricted assignment percent parameter, aircraft team routing algorithm, feasible route limit, feasible route objective, and assignment improvement quantity ratio. To assist the reader, Table 9 in Appendix A provides a notation guide.

4.1 Initial AMR Assignment Quantity

The intent of the initial AMR assignment is to conduct a broad search of the feasible assignment space established by the AMR assignment filter. An increase in the initial AMR assignment quantity, $\zeta \in \mathbb{Z}^+ = \{1, 2, 3, \ldots\}$, increases the likelihood of the aircraft team routing algorithm receiving sufficient assignments to generate feasible routes. Only assignments with feasible routes can enter the improvement cycle. On the other hand, an increase in ζ increases computation time in the aircraft team routing algorithm that might be more efficiently used in the heuristic's improvement cycle.

4.2 Unrestricted Assignment Percent Parameter

For the Army aviation air movement mission assignment, utilization, and routing problem, the best case solution is to support all AMRs with only low-cost helicopter teams. Of course, this is not possible for all scenarios. However, in an effort to explore the assignment space with an emphasis on assignments with all AMRs supported on low-cost helicopter teams, we introduce the unrestricted assignment percent parameter, $\eta \in [0, 100]$. This parameter specifies a percentage of the initial AMR assignment quantity, ζ, to allow random AMR assignment to any individually feasible helicopter team or to leave the AMR unsupported. For example, for an initial AMR assignment quantity $\zeta = 1000$ and unrestricted assignment percent parameter $\eta = 25$, only 250 of the initial AMR assignments would have the ability to assign AMRs to any individually feasible helicopter team, regardless of cost class, or leave some AMRs unsupported. The remaining 750 assignments would be restricted to assigning AMRs to only individually feasible low-cost helicopter teams.

4.3 Aircraft Team Routing Algorithm

The two aircraft team routing algorithms considered are the AMR insertion algorithm discussed in Nelson et al. (2023) and the AMR insertion algorithm with fuel insertion presented in this paper. The latter algorithm is an adaptation of the AMR insertion algorithm to increase refueling options. Both algorithms build on the advanced insertion algorithm described in Häme (2011). At each AMR insertion in the AMR insertion algorithm, the route's feasibility of AMR time windows, maximum passenger ride time, aircraft flight duration, aircraft capacity, aircraft latest return to the airport, and aircraft fuel level is checked. If one of these constraints is deemed infeasible, the route is not considered in the next AMR insertion. The AMR insertion algorithm assumes helicopter teams fully refuel at every HLZ with refuel capabilities. The algorithm creates a route with refuel stops only if an associated AMR pickup or drop-off at an HLZ with refuel capabilities exists. This feature reduces potential feasible routes and possible feasible AMR assignments.

The AMR insertion algorithm with fuel insertion (see Algorithm 1) introduced in this paper addresses the rigid refueling feature by allowing for refuel stops at HLZs with refuel capabilities regardless if there is an associated AMR pickup or drop-off at the HLZ. The AMR insertion algorithm with fuel insertion introduces two separate feasibility checks. Similar to the AMR insertion algorithm, the first-stage feasibility occurs after each AMR insertion. Unlike the AMR insertion algorithm, this adapted algorithm does not verify aircraft fuel level feasibility in the first-stage feasibility check. Instead, the first-stage feasibility check includes AMR time windows, maximum passenger ride time, aircraft flight duration, aircraft capacity, and aircraft's latest return to the airport feasibility. Only feasible routes are considered for the next AMR insertion. Upon insertion of all AMR pickups and drop-offs for the assigned AMRs to helicopter team k, the algorithm produces a set of complete first-stage feasible routes $S^k_{|N^k|}$, where N^k is the set of AMRs assigned to helicopter team k.

For each complete first-stage feasible route $s \in S^k_{|N^k|}$, the algorithm checks for aircraft team fuel feasibility. This is accomplished by ensuring that at every node j in complete route s, there is sufficient fuel to travel to node $j+1$. If there is insufficient fuel to travel to the next node, the algorithm inserts a refueling stop between nodes j and $j+1$. The algorithm selects the HLZ with refuel capabilities, not at node j or $j+1$ which minimizes the travel time from node j to the refuel node plus the travel time from the refuel node to node $j+1$ as the refuel stop. If there is not sufficient fuel at node j to travel to any HLZs with refueling capabilities, the complete route s is removed from $S^k_{|N^k|}$.

The fuel insertion function generates a set of fuel-feasible complete routes, but the potential fuel insertions may have changed the time structure of the route. The fuel-feasible complete routes must go through a second-stage feasibility check to ensure the feasibility of AMR time windows, maximum passenger ride time, aircraft flight duration, and aircraft's latest return to the airport. Notice that the second-stage feasibility differs from the first in that the aircraft capacity need not be checked. The algorithm assumes no passengers board or deplane at the refuel insertions. Upon completion of the second-stage feasibility check, the algorithm either has a set of fully feasible complete routes to calculate routing costs or an empty set of fully feasible complete routes in which the algorithm assigns infinite cost to the route associated with the AMR assignment.

Algorithm 1 AMR Insertion Algorithm with Fuel Insertion

Set $S_0^k = \{\emptyset\}$; $\quad$ (S_i^k = set of feasible service sequences with respect to AMRs $n_1^k, \ldots, n_{|N^k|}^k$ for helicopter team k)
for each $i \in \{n_1^k, ..., n_{|N^k|}^k\}$ **do**
    for each $s \in S_{i-1}^k$ **do**
        for each $h \in \{1, ..., |s|+1\}$ **do**
            for each $j \in \{h+1, ..., |s|+2\}$ **do**
                Set $r = I(s, i, h, j)$; $\quad$ (I= the insertion function)
                if service sequence r is 1st stage feasible **then**
                    $S_i^k = S_i^k \cup \{r\}$
                end if
            end for
        end for
    end for
    if $S_i^k = \emptyset$ **then**
        BREAK: Assign an infinite cost to route;
    end if
end for
for each $s \in S_{|N^K|}^k$ **do**
    Set $s = F(s)$; $\quad$ (F= the fuel insertion function)
    if service sequence s is 2nd stage feasible **then**
    else
        $S_{|N^K|}^k = S_{|N^K|}^k \backslash \{s\}$
    end if
end for
if $S_{|N^K|}^k = \emptyset$ **then**
    BREAK: Assign an infinite cost to route;
end if
for each $s \in S_{|N^K|}^k$ **do**
    Calculate routing cost $C(s)$
    Save minimum $C(s)$ as route cost for helicopter team k in assignment
    Save route associated with minimum $C(s)$
end for

4.4 Feasible Route Limit and Objective

Both the AMR insertion algorithm (Nelson et al. 2023) and the AMR insertion algorithm with fuel insertion in Section 4.3 have the ability to create the optimal helicopter team routing for a given AMR assignment. This is due to the fact that both algorithms can generate and evaluate every possible AMR route sequencing. However, the number of routes to evaluate becomes intractable as the number of assigned AMRs increases. In order to solve larger problems, it is necessary to limit the number of feasible routes carried forward for the next AMR insertion.

The methodology in which we select τ feasible routes after each AMR insertion iteration to carry forward to the next iteration builds on the work done by Häme (2011) and is discussed in Nelson et al. (2023). As the value of τ increases, so does the probability of generating a feasible route with a lower routing cost, but at an increased computational cost. We chose three candidate feasible route objectives to select the τ feasible routes to build upon at the next AMR insertion iteration. The first method chooses the τ routes with the smallest flight times. This is aligned with the third term of the problem's overall objective (Nelson et al. 2023, see Equation (1)) simplified here as,

$$\min \quad \alpha(\text{total unfulfilled AMRs}) + \sum_{\text{all teams}} (\beta^k \text{helicopter team usage}) + \sum_{\text{all teams}} \gamma^k (\text{flight time per team}) \quad (1)$$

and is shown in Equation (2). The other two feasible route objectives attempt to allow more flexibility in subsequent AMR insertions by choosing τ routes with either the maximum total slack time (3) or the maximum of the minimum slack times (4).
Given the routing sequence, $r = (r_1, \dots, r_m)$, we wish to minimize the time of flight (TOF),

$$f_{\text{TOF}}(r) = \sum_{j=1}^{m} t^k_{j-1,j}, \quad (2)$$

maximize the total slack time (TST),

$$f_{\text{TST}}(r) = \sum_{j=1}^{m} l_j - A^k_j(r), \quad (3)$$

or maximize the minimum slack time (MST),

$$f_{\text{MST}}(r) = \min_{j \in \{1,\dots,m\}} l_j - A^k_j(r), \quad (4)$$

where $t^k_{j,j'}$ is the time between nodes j and j' for helicopter team k, l_j is the latest arrival time for the AMR j, and $A^k_j(r)$ is the calculated time of arrival at node j.

4.5 Assignment Improvement Quantity Ratio

The improvement cycle attempts to improve y assignments with the lowest overall objective values by attempting to shift unsupported AMRs to helicopter teams. An increase in y provides a greater opportunity to improve more initial assignments and therefore increase the potential to result in a better overall solution. A larger y also results in increased computation time and potentially less of the assignment space explored. We control the value of y by using parameter $\theta \in [0, 1]$ such that $y = \lfloor \theta\zeta \rfloor$, where ζ is the initial AMR assignment quantity and $\lfloor x \rfloor = \max\{z \in \mathbb{Z} | z \leq x\}$.

5 Heuristic Improvement Design of Experiments

5.1 Sequential Experiments

Gunawan et al. (2011) describe a sequential experimental approach to tune algorithm parameters. The approach includes screening, exploration, and exploitation phases to further tune parameters in order to improve algorithm performance. Figure 2 illustrates the air movement operations planning heuristic parameter tuning DOE procedure. The purpose of the design of experiments (DOE) is to analyze heuristic performance while varying the heuristic parameters in order to identify the best heuristic parameter settings. We design two scenarios with dissimilar HLZ networks and AMR demand to represent utility helicopter unit air movement operations. We tune the heuristic parameters under each scenario and compare the resulting heuristic with tuned parameter settings performance. The interested reader can find the DOEs, phase results, and additional details in Nelson (2023) (see Ch. 3 and App C).

The heuristic improvement DOE is a controlled set of tests designed to model and explore the relationship between the heuristic parameters and response variable (JMP & Proust 2017, Montgomery 2017). The

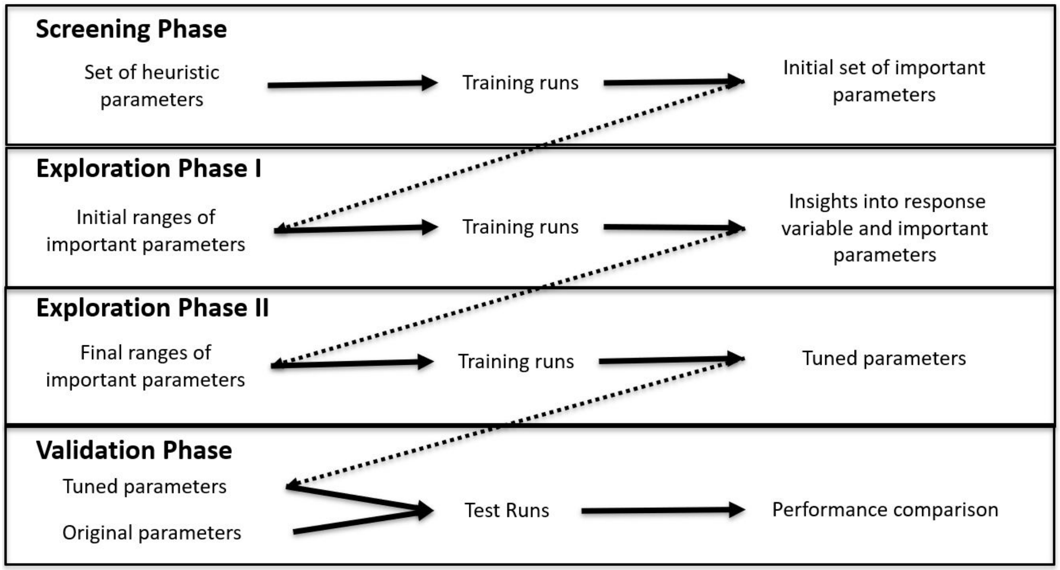

Figure 2: Air Movement Operations Planning Heuristic Parameter Tuning DOE Procedure. Conceptualization by authors.

primary response variable is the resulting overall objective value. Further analysis of the components of the overall objective value includes quantity and priority level of unsupported AMRs, aircraft team utilization penalty, and total flight time. The DOE sizes allow for 80% power for all main effects, second-degree interactions, and quadratic effects of all discrete numeric and continuous effects with 95% confidence for each phase.

Table 1: Parameters to Tune

Parameter	Data Type
Initial AMR Assignment Quantity (ζ)	Discrete Numeric
Unrestricted Assignment Percent Parameter (η)	Continuous
Aircraft Team Routing Algorithm	Categorical
Feasible Route Limit (τ)	Discrete Numeric
Feasible Route Objective	Categorical
Assignment Improvement Ratio (θ)	Continuous

5.1.1 Heuristic Objective and Penalty Weights

The objective of the heuristic is to minimize the sum of weighted penalties of unsupported AMRs, helicopter team utilization, and flight time. A heuristic objective formula that represents the mixed integer linear programming objective in Nelson et al. (2023) is shown in Equation (5). The first summation in the objective accounts for the penalty of leaving AMRs unsupported. Let α be the unsupported penalty weight, b_i be the transformed AMR priority for AMR i, and Π_i be the binary variable with value 1 if AMR i is unsupported and 0 if supported. The second summation in the objective describes the penalties for helicopter team utilization and total flight time. Let β^k represent the utilization penalty for helicopter team k and Υ^k be the binary variable with value 1 if helicopter team k is assigned one or more AMRs and 0 if assigned zero AMRs to support. Let γ^k be the flight hour penalty for helicopter team k and Φ^k be the total flight hours for helicopter team k.

$$\min \alpha \sum_{i \in n} b_i \Pi_i + \sum_{k \in K} (\beta^k \Upsilon^k + \gamma^k \Phi^k) \tag{5}$$

Similar to the practical application in Nelson et al. (2023), the AMR priority level in this DOE is transformed through an exponential function with base $B = 2$. This implies that an AMR of one higher level priority is twice as important as an AMR of the priority level below. Let p_i be the priority level of AMR i as referenced in Table 10. Then $b_i = 2^{(9-p_i)}$. We set the unsupported penalty weight $\alpha = 100$, which can be interpreted as leaving an unsupported priority level 9 AMR as equivalent to logging 100 flight hours on a helicopter team with $\gamma^k = 1$. Setting α at a high value sets a priority of supporting all AMRs. The utilization penalty for each aircraft team β^k is a calculated value used to balance the commander's assessed cost of committing an aviation asset versus leaving an AMR unsupported. The calculation follows as $\alpha b_i = \alpha B^{(9-p_i)} = \beta^k$. Given the commander's AMR priority level threshold to launch a particular aircraft team for support, it is possible to calculate β^k. This concept is discussed further in Section 6.2.2.

We define the expected AMR flight time for a given scenario as

$$\text{E[flight time]} = \sum_{\iota=1}^{\Upsilon} \sum_{\kappa=1}^{\Upsilon} P(\text{pickup} = \iota) P(\text{drop} = \kappa | \text{pickup} = \iota) t_{\iota\kappa}, \tag{6}$$

where the HLZs are in the set $(1, ..., \Upsilon)$, $P(\text{pickup} = \iota)$ is the probability an AMR will originate at HLZ ι, $P(\text{drop} = \kappa | \text{pickup} = \iota)$ is the conditional probability the AMR drops off at HLZ κ given the AMR picks up at HLZ ι, and $t_{\iota\kappa}$ is the flight time from HLZ ι to HLZ κ.

6 Scenarios

6.1 Summary

We design two scenarios to tune the heuristic procedure with key differences in HLZ network scale and overall AMR volume. For each scenario, we define the HLZ network, refuel nodes, helicopter fleets, and AMR demand characteristics with identical distribution assumptions from Nelson et al. (2023). The first scenario is a low-density operational environment set in Afghanistan whereas the second scenario features small urban environment set in Baghdad, Iraq, serving a higher AMR volume. The expected AMR flight time of the Baghdad scenario is 0.1335 hours, which differs significantly from that of the Afghanistan scenario's expected AMR flight time of 0.51 hours. Table 2 summarizes the major differences between the scenarios with the subsequent sections providing specific details.

Table 2: Scenario Summary

Scenario Feature	RC-N, Afghanistan	Baghdad, Iraq
AMR Quantity	30	50
Expected AMR Flight Time (hrs)	0.51	0.1335
Max Flight Time (hrs)	2.389	0.282
Number of HLZs	10	10
Number of Refuel Nodes	5	2

6.2 Low-density Scenario: Regional Command-North, Afghanistan

6.2.1 HLZ Network

The HLZ network is a two-thirds scaled representation of Regional Command North, Afghanistan. The scaling is in order to allow the helicopter fleet to support a larger number of AMRs and thus further test the heuristic's capabilities. As seen in Figure 3, there are ten helicopter landing zones, of which five have refueling capabilities. HLZs M and Z are hubs, serving as the pickup or drop-off HLZ for many AMRs.

6.2.2 Helicopter Fleet

The helicopter fleet consists of six UH-60 Blackhawk helicopter teams stationed at HLZ M. Table 3 displays the helicopter team features. All teams have identical maximum passenger capacity, average cruising speed,

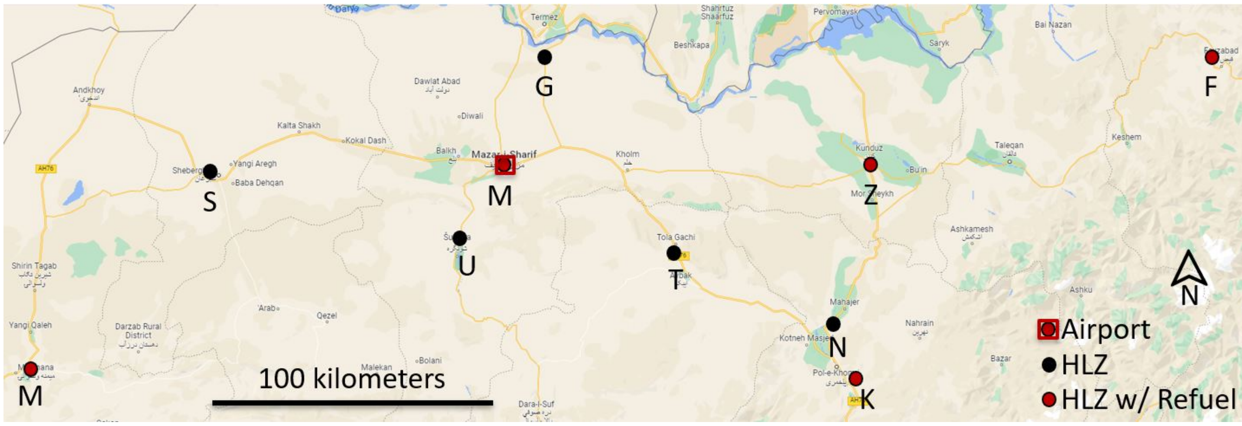

Figure 3: (color online) HLZ network for the scenario set in Regional Command North, Afghanistan (note: two-thirds scale).
Figure by authors adapted from Google Maps.

and fuel capacity. There are two teams designated as AM with a flight window of 0700–1500. The two PM teams have a flight window of 1500–2100. Note that we assume the PM teams fly part of their mission under night vision goggles and therefore have a maximum duration of 6 hours as opposed to the day-only AM team with a maximum duration of 8 hours. The Quick Reaction Force (QRF) teams straddle the AM and PM teams' time windows with a flight window from 1100–1900 and an 8-hour maximum duration.

Table 3: Regional Command - North Scenario Helicopter Fleet

Team	Earliest Departure	Latest Arrival	Max Duration	Max Capacity	Speed (km/hr)	Fuel (hours)	Utilization Penalty (β)	Flight Hour Penalty (γ)
UH_AM_A	0700	1500	8	22	222.2	2	1	1
UH_AM_B	0700	1500	8	22	222.2	2	1	1
UH_PM_A	1500	2100	6	22	222.2	2	1	1
UH_PM_B	1500	2100	6	22	222.2	2	1	1
UH_QRF_A	1100	1900	8	22	222.2	2	400	1
UH_QRF_B	1100	1900	8	22	222.2	2	400	1

The two helicopter teams designated with QRF can be considered high-cost teams. QRF helicopter teams are commonly used teams held in reserve, with crews that can rapidly react to any commander-directed missions. QRF teams are given air movement operation missions only when the commander deems the mission is of high enough priority to commit the reserve QRF asset. For this reason, the QRF helicopter teams are given a utilization penalty $\beta^k = 400$. This utilization penalty can be interpreted as the commander setting the QRF launch threshold equivalent to not supporting a level 7 priority (O-6 Colonel or Equivalent), two priority level 8 AMRs, or four priority level 9 AMRs since $\beta^k = 400 = (100)2^{(9-7)} = (100)(2)2^{(9-8)} = (100)(4)2^{(9-9)}$, $\forall k$.

6.2.3 Air Mission Requests

For each run in the DOE, the number of AMRs is $n = 30$. The number of AMRs is set to stretch the limits of the low-cost helicopter teams in their ability to support the demand in a moderately large HLZ network. While each run has a fixed number of AMRs, the features of each run's AMRs will differ. HLZs M and Z are hub HLZs serving as the pickup or drop off HLZ for many AMRs. The AMR feature distributions follow the practical application in Nelson et al. (2023). Table 11 displays the Afghanistan scenario's AMR HLZ pickup and drop-off probabilities.

The number of passengers per AMR is equally distributed between the integers from one to eleven. Each AMR has a 25% probability of having a priority level of 9, and a 25% probability of having a priority level of 8, with the remaining probability equally distributed among priority levels 1 to 7. Finally, each AMR is assigned a time window with equal probability for windows 0700–2100, 1200–1700, or 1700–2100. Finally, the maximum passenger ride time L is set at 4 hours.

6.3 High-density Scenario: Baghdad, Iraq

6.3.1 HLZ Network

The Baghdad scenario HLZ network is a true-to-scale representation of the Multi-National Division-Baghdad, Iraq. As seen in Figure 4, the network consists of ten HLZs of which HLZs T and B have refueling capabilities. HLZs T, B, and L are hubs, serving as the pickup or drop-off HLZs for many AMRs.

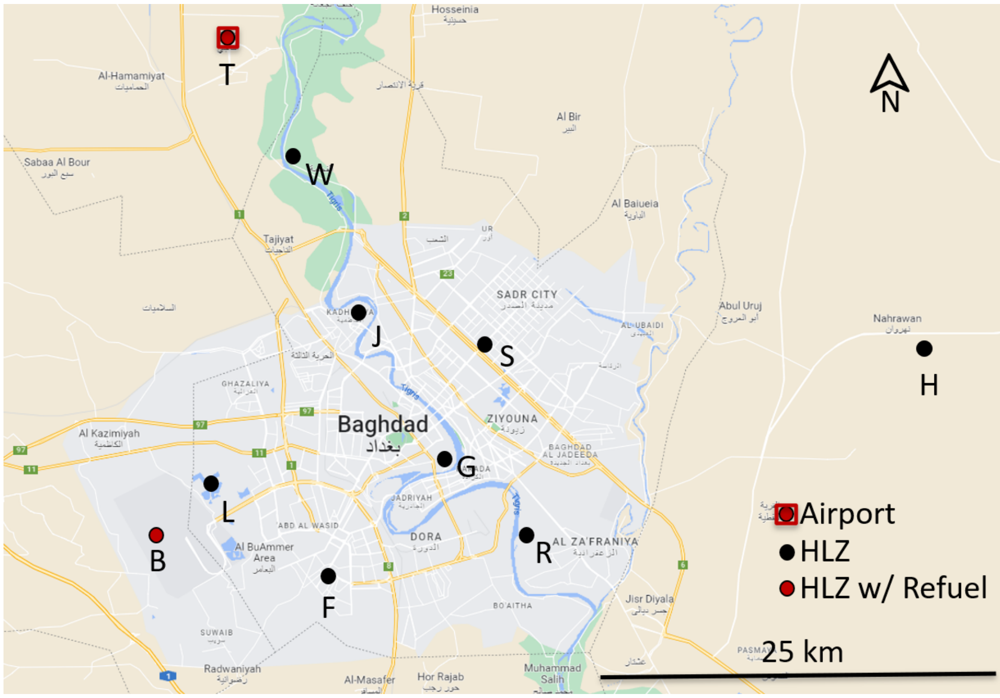

Figure 4: (color online) HLZ network for the scenario set in Baghdad, Iraq (note: true-to-scale). Figure by authors adapted from Google Maps.

6.3.2 Helicopter Fleet

The helicopter fleet consists of six UH-60 Blackhawk helicopter teams stationed at HLZ T. The fleet is identical to the Afghanistan Scenario fleet shown in Table 3 with speed as an exception. Due to the condensed nature of the HLZ network, helicopters travel slower on average in Baghdad than in a more spread-out HLZ network with speeds for all aircraft teams set to 185.2 (km/hr).

6.3.3 Air Mission Requests

For each run in the design of experiments, the number of AMRs is $n = 50$. The number of AMRs is set to stretch the limits of the helicopter teams in their ability to support the demand even with high-cost QRF aircraft teams. HLZs T, B, and L are hub HLZs, serving as the pickup and drop-off HLZ for many AMRs. Due to the proximity of HLZs B and L and the fact they share a common forward operating base, there are no AMRs between the two HLZs. Table 12 depicts the AMR HLZ pickup and drop-off probabilities for the Baghdad scenario. The expected AMR flight time of the Baghdad scenario is 0.1335 hours, which differs significantly from that of the Afghanistan scenario's expected AMR flight time of 0.51 hours.

The assignment of the number of passengers, priority level, and flight window for each AMR follows the Afghanistan scenario methodology as discussed in Section 6.2. Additionally, like the Afghanistan scenario, the maximum passenger ride time L is set at 4 hours.

7 Heuristic Improvement Results

The heuristic improvement DOE sought to tune heuristic parameter settings in order to produce superior solutions to the Army aviation air movement mission assignment, utilization, and routing problem and improve on the heuristic presented by Nelson et al. (2023). During the initial experiments for the Afghanistan scenario, a feasible route limit (τ) of 1 was not considered a good value and thus excluded in the initial screening range. Subsequent exploration phases showed $\tau = 1$ to be the best value. With this in mind, the Screening phase for the Baghdad scenario included this value in the initial DOE range for τ. The impact of this change removed any reason to do a second Explore phase for the Baghdad scenario.

As shown Tables 4–5, the rigorous DOE process arrived at heuristic parameters tuned to two separate scenarios. The heuristic with tuned parameter settings resulted in solutions with lower objective values than those with its original settings. The tuned parameter settings in both scenarios provided statistically significant evidence of superior performance. Furthermore, the tuned parameter settings gained through separate scenario data sets, although slightly different, proved to produce similar solutions for both scenarios. Hence, using parameter settings tuned with Afghanistan scenario or Baghdad scenario training data is equally beneficial. The interested reader may consult Appendix B for details on solution quality over time.

The motivated reader may find the instances for these DOEs and associated heuristic solutions in Nelson (2023, Appendix C, pp.114–136).

Table 4: Heuristic Tuning Results for the Afghanistan Scenario. Final tuned values are shown in the "Validate" column.

Parameter	Screening Phase	Explore I	Explore II	Validate
Initial AMR Assignment Quantity (ζ)	$[500, 10000]$	$[3000, 7000]$	7000	7000
Unrestricted Assignment Percent Parameter (η)	$[50, 100]$	75	75	75
Aircraft Team Routing Algorithm	Constructive, Fuel Insertion	Fuel Insertion	Fuel Insertion	Fuel Insertion
Feasible Route Limit (τ)	$[10, 500]$	$[5, 50]$	$[1, 5]$	1
Feasible Route Objective	TOF, TST, MST	TST, MST	TST	TST
Assignment Improvement Ratio (θ)	$[0.01, 0.1]$	0.01	0.01	0.01
Scenario Runs	100	40	40	30
Time per Run (min)	60	60	60	60

Table 5: Heuristic Tuning Results for the Baghdad Scenario. Final tuned values are shown in the "Validate" column.

Parameter	Screening Phase	Explore	Validate
Initial AMR Assignment Quantity (ζ)	$[500, 10000]$	10000	10000
Unrestricted Assignment Percent Parameter (η)	$[50, 100]$	50	50
Aircraft Team Routing Algorithm	Constructive, Fuel Insertion	Constructive, Fuel Insertion	Fuel Insertion
Feasible Route Limit (τ)	$[1, 500]$	$[1, 10]$	1
Feasible Route Objective	TOF, TST, MST	TOF, TST, MST	TOF
Assignment Improvement Ratio (θ)	$[0.01, 0.1]$	0.01	0.01
Scenario Runs	100	40	30
Time per Run (min)	60	60	60

To measure the improvement, we measure the objective value of the original heuristic from Nelson et al. (2023) and the tuned validation settings for each of the 30 validation instances. Let D be the associated

Table 6: Original heuristic settings from Nelson et al. (2023) and final tuned settings for each scenario.

Parameter	Original (Nelson et al. 2023)	Afghanistan Tuned	Baghdad Turned
Initial AMR Assignment Quantity (ζ)	5000	7000	10000
Unrestricted Assignment Percent Parameter (η)	100	75	50
Aircraft Team Routing Algorithm	Constructive	Fuel Insertion	Fuel Insertion
Feasible Route Limit (τ)	10	1	1
Feasible Route Objective	TOF	TST	TOF
Assignment Improvement Ratio (θ)	0.01	0.01	0.01

difference in objective values using Equation (5) and let μ_D be the true mean difference. Our null and alternate hypotheses are then

$$H_0 : \mu_D = 0$$
$$H_a : \mu_D > 0$$

where $\mu_D > 0$ indicates the objective value of the original settings is greater than the tuned settings. We conduct a paired t-test (Devore 2016) for both scenarios using a significance level $\alpha = 0.05$; Table 7 provides the paired t-test results showing both sets of parameters result in improvement over the original parameters.

For the Afghanistan scenario, 19 of 30 instances result in the tuned settings using one less high-cost QRF helicopter. The tuned parameters result in an lower objective value overall in 26 instances; in the four instances where this was not the case, the average difference was only 0.867 flight hours. On average the Baghdad-tuned settings supported all AMRs in all 30 instances where the original settings left 2.33 AMRs unsupported on average.

Numerical experiments with both tuned settings show similar performance both in terms of number of AMRs supported and total flight time. Using parameter settings turned with either the Afghanistan or Baghdad scenario seems to be equally beneficial. The interested reader can review the numerical experiments in Nelson (2023, App C).

Table 7: Paired T-test results comparing validation heuristic settings for each scenario to the original heuristic parameters from Nelson et al. (2023).

Improvement Over Original: Afghanistan Scenario		Improvement Over Original: Baghdad Scenario	
D	p-value	D	p-value
259	1.54×10^{-8}	344.4	3.66×10^{-12}

8 Application-Sized Problem

8.1 Overview

Nelson et al. (2023) provide an application-sized problem as a proof of concept of the heuristic's ability to generate feasible assignment and routing solutions in a time period useful to aviation mission planners. We now seek to generate comparable solutions in a condensed time period with tuned parameter settings on the identical scenario from Nelson et al. (2023). The heuristic uses the Afghanistan scenario tuned parameter settings described in Table 4. Actual problem instances are available from Daniels et al. (2023).

8.2 Results

Table 8 provides the results and performance of the heuristic with original parameter settings and heuristic with Afghanistan scenario-tuned parameter settings on application-sized problems. Both heuristics were able to find feasible solutions, supporting all AMRs for all instances in both 90 AMR and 100 AMR quantity-sized problems. The utilization and AMR support were identical for both heuristics. On average, the heuristic with tuned parameter settings arrived at assignment and routing solutions with 1.46 more hours of flight time, a 7.1% average increase. However, the heuristic with tuned parameter settings arrived at a solution in 22 minutes on average compared to the average 221-minute execution time for the heuristic with original parameter settings. The drastically reduced execution time with minimal solution quality degradation provides aviation mission planners with opportunities to generate multiple courses of action and perform additional mission analysis in a shortened mission planning cycle.

9 Conclusion

This paper sought to improve the air movement operations planning heuristic in order to generate superior solutions in less time. Through developing alternative modular methodologies and a rigorous design

Table 8: Application sized problem results with (left) heuristic from Nelson et al. (2023) and (right) tuned settings from this paper.

n	Instance	Heuristic with Original Parameter Settings from Nelson et al. (2023)					Heuristic with Afghanistan Scenario Tuned Parameter Settings				
		Time (s)	Objective	Unsupported	Utilization	Route Time	Time (s)	Objective	Unsupported	Utilization	Route Time
90	1	13326	30.80	0	10	20.80	1616	31.34	0	10	21.34
90	2	10364	29.87	0	10	19.87	954	32.09	0	10	22.09
90	3	5086	31.15	0	10	21.15	689	30.62	0	10	20.62
90	4	12134	29.10	0	10	19.10	1681	31.29	0	10	21.29
90	5	10085	30.51	0	10	20.51	1048	30.99	0	10	20.99
90	6	3654	31.73	0	10	21.73	405	34.60	0	10	24.60
90	7	11996	30.48	0	10	20.48	1288	31.36	0	10	21.36
90	8	7375	29.77	0	10	19.77	801	32.84	0	10	22.84
90	9	11304	29.36	0	10	19.36	1239	30.36	0	10	20.36
90	10	8280	28.88	0	10	18.88	800	31.00	0	10	21.00
100	1	14755	31.59	0	10	21.59	1180	33.06	0	10	23.06
100	2	19265	30.81	0	10	20.81	2404	32.26	0	10	22.26
100	3	15124	30.57	0	10	20.57	1461	31.78	0	10	21.78
100	4	19538	29.11	0	10	19.11	2145	31.42	0	10	21.42
100	5	19929	33.83	0	10	23.83	1107	35.23	0	10	25.23
100	6	20680	30.23	0	10	20.23	2416	31.06	0	10	21.06
100	7	20360	32.17	0	10	22.17	943	33.64	0	10	23.64
100	8	8531	32.52	0	10	22.52	803	34.38	0	10	24.38
100	9	15634	31.28	0	10	21.28	786	32.62	0	10	22.62
100	10	17654	29.49	0	10	19.49	2214	30.54	0	10	20.54

of experiments based heuristic parameter tuning, we arrived at a fine-tuned heuristic with an average 33% objective improvement over the original heuristic described in Nelson et al. (2023) The bulk of the objective improvement resulted from the reduced utilization of high-cost helicopter teams in the Afghanistan validation data set and through superior AMR support in the Baghdad validation data set. Improvements of this nature preserve costly and scarce Army aviation, maintenance, and personnel assets while providing more services to supported units. Reduced high-cost aircraft team utilization frees the teams to conduct other command-directed missions and ultimately provides superior capabilities to the supported ground commanders. Additionally, during the Afghanistan scenario validation phase, the fine-tuned heuristic was able to provide a feasible solution in an average of 8.03 minutes, which is a 70% reduction in time compared to the original heuristic. Rapidly generated solutions enhance aviation mission planners' ability to quickly generate courses of action to meet the commander's requirements. The dramatically reduced computation time also makes it feasible to employ distinct parameter sets for the objective function (e.g., $\alpha, B, \beta^k, \gamma^k$) to quickly generate multiple courses of action (COAs) for further analysis and/or refinement by the planners (Nelson et al. 2022).

There are many opportunities to further improve the air movement operations planning heuristic. It is reasonable to believe parallelization of the aircraft team routing process would significantly improve computational speed. Additionally, the heuristic should output useful products for the Army aviation mission planner and operator. To add additional sophistication, the heuristic could introduce flight characteristics associated with altitude and air temperature. Finally, beyond solving the Army aviation air movement mission assignment, utilization, and routing problem, this heuristic has the potential to be integrated into additional decision support models, including determining the best allocation of aviation resources to task forces.

Disclaimer

Lieutenant Colonel Russell Nelson's contribution was performed as part of his official duties as an employee of the United States Government. The views expressed in this paper are those of the authors and do not reflect the official policy or position of the United States Army, the Department of Defense, or the United States Government.

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References

Beelen, H., Bergveld, H. J. & Donkers, M. (2020), 'Joint estimation of battery parameters and state of charge using an extended kalman filter: A single-parameter tuning approach', *IEEE Transactions on Control Systems Technology* **29**(3), 1087–1101.

Cordeau, J.-F. & Laporte, G. (2007), 'The dial-a-ride problem: Models and algorithms', *Annals of Operations Research* **153**(1), 29–46. https://link.springer.com/article/10.1007/s10479-007-0170-8.

Daniels, R., Nelson, R., McConnell, B. & Thoney-Barletta, K. (2023), 'US Army Aviation Air Movement Request Problem Instances', Dryad Repository. Dataset, https://doi.org/10.5061/dryad.zpc866tcx.

de Alvarenga Rosa, R., Machado, A. M., Ribeiro, G. M. & Mauri, G. R. (2016), 'A mathematical model and a clustering search metaheuristic for planning the helicopter transportation of employees to the production platforms of oil and gas', *Computers & Industrial Engineering* **101**, 303–312. https://doi.org/10.1016/j.cie.2016.09.006.

Department of the Army [DA] (2020*a*), *ATP 3-04.1 Aviation Tactical Employment*, Army Publishing Directorate, Headquarters Department of the Army, Washington DC.

Department of the Army [DA] (2020*b*), *FM 3-04 Army Aviation*, Army Publishing Directorate, Headquarters Department of the Army, Washington DC. https://armypubs.army.mil/epubs/DR_pubs/DR_a/pdf/web/ARN21797_FM_3-04_FINAL_WEB_wfix.pdf.

Devore, J. L. (2016), *Probability and Statistics for Engineering and the Sciences*, Cengage Learning.

Espinoza, T. J. (2022), 'Re: Air Movement Operations Planning Model Update', Email correspondence. 23 Oct 2022.

Gunawan, A., Lau, H. C. & Lindawati (2011), Fine-tuning algorithm parameters using the design of experiments approach, *in* 'International conference on learning and intelligent optimization', Vol. 6683, Springer, Berlin, Germany, pp. 278–292. https://doi.org/10.1007/978-3-642-25566-3_21.

Häme, L. (2011), 'An adaptive insertion algorithm for the single-vehicle dial-a-ride problem with narrow time windows', *European Journal of Operational Research* **209**(1), 11–22.

Ho, S. C., Szeto, W. Y., Kuo, Y.-H., Leung, J. M., Petering, M. & Tou, T. W. (2018), 'A survey of dial-a-ride problems: Literature review and recent developments', *Transportation Research Part B: Methodological* **111**, 395–421. https://doi.org/10.1016/j.trb.2018.02.001.

JMP, A. & Proust, M. (2017), *JMP 13 Design of experiments guide, 2nd edition*, SAS Institute, Inc., Cary, NC.

Lujan-Moreno, G. A., Howard, P. R., Rojas, O. G. & Montgomery, D. C. (2018), 'Design of experiments and response surface methodology to tune machine learning hyperparameters, with a random forest case-study', *Expert Systems with Applications* **109**, 195–205. https://doi.org/10.1016/j.eswa.2018.05.024.

Mogensen, M. D. (2014), Service network design optimization for Army Aviation lift planning, Master's thesis, Massachusetts Institute of Technology, Cambridge, MA. http://hdl.handle.net/1721.1/90066.

Montgomery, D. C. (2017), *Design and Analysis of Experiments*, John Wiley & Sons, Hoboken, NJ.

Nasri, S., Bouziri, H. & Aggoune-Mtalaa, W. (2021), Customer-oriented dial-a-ride problems: A survey on relevant variants, solution approaches and applications, *in* 'Emerging Trends in ICT for Sustainable Development', Springer, Cham, Switzerland, pp. 111–119. Proceedings of the NICE2020 International Conference, https://doi.org/10.1007/978-3-030-53440-0.

Nelson, R. (2023), Operations Research Applications in US Army Aviation Air Movement Operations, PhD thesis, North Carolina State University, Raleigh, NC. https://www.lib.ncsu.edu/resolver/1840.20/40868.

Nelson, R., Espinoza, T. & McConnell, B. M. (2022), 'Army Aviation Air Movement Automation for the Mission Planner', *Aviation Digest* **10**(1), 38–39. https://www.lib.ncsu.edu/resolver/1840.20/39678.

Nelson, R., King, R., McConnell, B. M. & Thoney-Barletta, K. (2023), 'US Army Aviation Air Movement Operations Assignment, Utilization, and Routing', *Journal of Defense Analytics and Logistics* **7**(1), 2–28. https://doi.org/10.1108/JDAL-11-2022-0013.

O'Connor, D. & English, N. J. (2021), 'Systematic design-of-experiments, factorial-design approaches for tuning simple empirical water models', *Molecular Simulation* **47**(2-3), 119–130.

Rao, R. V. & Kalyankar, V. D. (2013), 'Parameter optimization of modern machining processes using teaching–learning-based optimization algorithm', *Engineering Applications of Artificial Intelligence* **26**(1), 524–531.

Shankar, R. B., Mistry, E. D., Lubert-Perquel, D., Nevjestic, I., Heutz, S. & Petit, C. (2022), 'A response surface model to predict and experimentally tune the chemical, magnetic and optoelectronic properties of oxygen-doped boron nitride', *ChemPhysChem* **23**(13). https://doi.org/10.1002/cphc.202100854.

Sundar, K. & Rathinam, S. (2012), Route planning algorithms for unmanned aerial vehicles with refueling constraints, *in* '2012 American Control Conference (ACC)', IEEE, Montreal, Canada, pp. 3266–3271. 27–29 June 2012, https://doi.org/10.1109/ACC.2012.6315620.

Sundar, K., Venkatachalam, S. & Rathinam, S. (2016), Formulations and algorithms for the multiple depot, fuel-constrained, multiple vehicle routing problem, *in* '2016 American Control Conference (ACC)', IEEE, Boston, MA, pp. 6489–6494. 6–8 July 2016, https://doi.org/10.1109/ACC.2016.7526691.

Wang, H., Qiu, Z., Su, S., Jia, S., Li, Y., Liu, X., Zheng, H. & Liang, D. (2020), 'Parameter optimization framework on wave gradients of wave-caipi imaging', *Magnetic resonance in medicine* **83**(5), 1659–1672.

Yang, B., Yu, T., Zhang, X., Huang, L., Shu, H. & Jiang, L. (2018), 'Interactive teaching–learning optimiser for parameter tuning of VSC-HVDC systems with offshore wind farm integration', *IET Generation, Transmission & Distribution* **12**(3), 678–687.

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A Additional Information

A.1 Notation Guide

Table 9: Notation Guide (in order of appearance)

β^k	utilization penalty for aircraft team k, $\beta^k = \alpha B^{(9-p_i)} = \alpha b_i$
y	$y = \lfloor \theta\zeta \rfloor$
$\zeta \in \mathbb{Z}^+$	initial AMR assignment quantity
$\eta \in [0, 100]$	unrestricted assignment percent parameter
$S^k_{\lvert N^k \rvert}$	set of complete first-stage feasible routes
N^k	set of AMRs assigned to helicopter team k
τ	number of feasible routes after each AMR insertion iteration to carry forward to the next iteration
$f_{\text{TOF}}(r)$	time of flight (TOF) for route sequence r
$f_{\text{TST}}(r)$	total slack time (TST) for route sequence r
$f_{\text{MST}}(r)$	minimum slack time (MST) for route sequence r
l_j	latest arrival time for AMR j
$t^k_{j,j'}$	time between nodes j and j' for helicopter team k
$A^k_j(r)$	calculated time of arrival at node j
$\theta \in [0, 1]$	assignment improvement quantity ratio
α	unsupported AMR penalty
b_i	transformed AMR priority for AMR i, $b_i = B^{(9-p_i)}$
Π_i	binary variable with value 1 if AMR i is unsupported and 0 otherwise
Υ^k	binary variable with value 1 if helicopter team k is assigned one or more AMRs and 0 otherwise
γ^k	flight hour penalty for helicopter team k
Φ^k	total flight hours for helicopter team k
B	base for exponential transformation of doctrinal AMR priority level
p_i	doctrinal AMR priority level from Table 10
L	maximum ride time (hours)

Table 10: Air Mission Request Priority (p_i) (Mogensen 2014).

AMR Mission	Priority (p_i)
Downed Aircraft Recovery	1 (highest)
Emergency Leave	2
General Officer Movement	3
Military Working Dog	4
Critical Equipment Repair	5
Religious Services	6
O-6 Colonel or Equivalent	7
Rest & Recovery Leave	8
Other	9 (lowest)

A.2 Scenario Details

Table 11: Afghanistan Scenario AMR HLZ Pickup and Drop Off Probabilities.

HLZ	Probability Pickup	Probability Drop Off Given Pickup HLZ									
		M	A	S	U	G	Z	T	N	K	F
M	1/4	0	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9
A	1/16	1/4	0	1/14	1/14	1/14	1/4	1/14	1/14	1/14	1/14
S	1/16	1/4	1/14	0	1/14	1/14	1/4	1/14	1/14	1/14	1/14
U	1/16	1/4	1/14	1/14	0	1/14	1/4	1/14	1/14	1/14	1/14
G	1/16	1/4	1/14	1/14	1/14	0	1/4	1/14	1/14	1/14	1/14
Z	1/4	1/9	1/9	1/9	1/9	1/9	0	1/9	1/9	1/9	1/9
T	1/16	1/4	1/14	1/14	1/14	1/14	1/4	0	1/14	1/14	1/14
N	1/16	1/4	1/14	1/14	1/14	1/14	1/4	1/14	0	1/14	1/14
K	1/16	1/4	1/14	1/14	1/14	1/14	1/4	1/14	1/14	0	1/14
F	1/16	1/4	1/14	1/14	1/14	1/14	1/4	1/14	1/14	1/14	0

Table 12: Baghdad Scenario AMR HLZ Pickup and Drop Off Probabilities.

HLZ	Probability Pickup	Probability Drop Off Given Pickup HLZ									
		T	B	L	W	F	G	R	S	J	H
T	1/6	0	1/4	1/4	1/14	1/14	1/14	1/14	1/14	1/14	1/14
B	1/6	1/3	0	0	2/21	2/21	2/21	2/21	2/21	2/21	2/21
L	1/6	1/3	0	0	2/21	2/21	2/21	2/21	2/21	2/21	2/21
W	1/14	1/6	1/6	1/6	0	1/12	1/12	1/12	1/12	1/12	1/12
F	1/14	1/6	1/6	1/6	1/12	0	1/12	1/12	1/12	1/12	1/12
G	1/14	1/6	1/6	1/6	1/12	1/12	0	1/12	1/12	1/12	1/12
R	1/14	1/6	1/6	1/6	1/12	1/12	1/12	0	1/12	1/12	1/12
S	1/14	1/6	1/6	1/6	1/12	1/12	1/12	1/12	0	1/12	1/12
J	1/14	1/6	1/6	1/6	1/12	1/12	1/12	1/12	1/12	0	1/12
H	1/14	1/6	1/6	1/6	1/12	1/12	1/12	1/12	1/12	1/12	0

B Solution Quality Over Time

B.1 Overview

During heuristic improvement through parameter tuning design of experiments, we fixed each run at 60 minutes. Throughout the run time, the heuristic had the ability to update the solution and improve the overall objective. We chose the 60-minute run time as a time frame that would be acceptable for an aviation air mission operations planner during typical operational conditions. We also analyze how the quality of the solution improves over a longer period of time. This will give further insight into how the mission planner could choose to use the air movement operations planning heuristic based on mission and planning conditions.

In this analysis, we use the heuristic with Afghanistan scenario tuned heuristic parameter settings as described in Table 6. We allow the heuristic to run for six hours on each of the thirty Afghanistan Scenario validation data runs described in Section 6.2.

B.2 Results

Figure 5 displays the results of the quality of solution over time analysis. The lines show the best objective values for each of the 30 runs over the six-hour execution time. An objective value decrease of 400 or more represents a solution that uses one less high-cost QRF helicopter team. Smaller objective value decreases are gained through route time improvements. The graph shows five runs that had significant objective value improvements (a decrease of at least 400) after the 60-minute mark. This leaves the heuristic obtaining the best solution for twenty-five of the thirty runs within the first hour. Furthermore, the heuristic obtained its best solution for all runs within 150 minutes. Following the results of this analysis, the aviation mission planner should have confidence that a 60-minute run time will have greater than 83% probability (confidence interval $[65.3\%, 94.4\%]$) of finding the best heuristic solution and even greater probability (confidence interval $[88.4\%, 100\%]$) with a 150 minute run time.

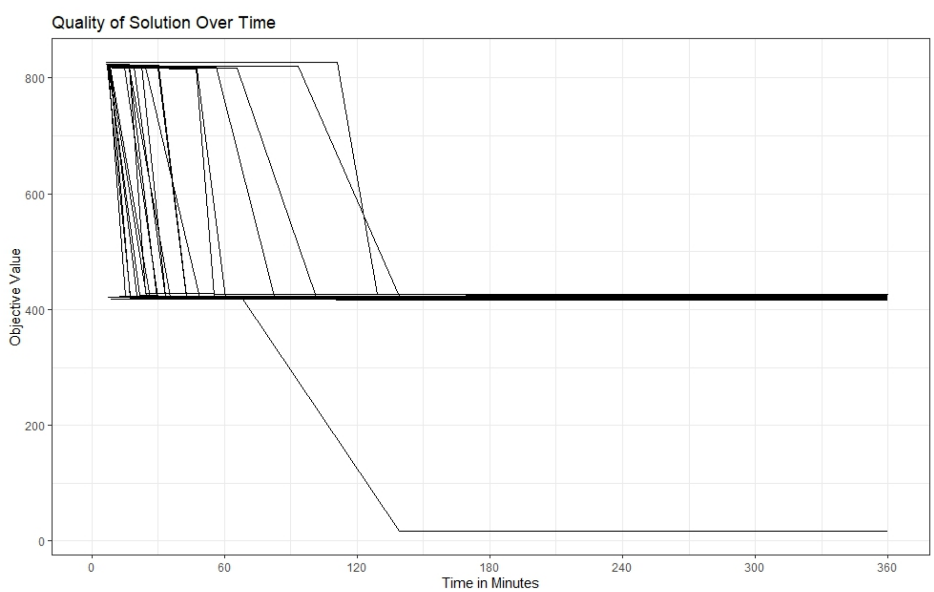

Figure 5: Afghanistan Validation Runs Quality of Solution Over Time.