Heuristics for Multi-Vehicle Routing Problem Considering Human-Robot Interactions

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Abstract—Autonomous mobile robots (AMRs) are being used extensively in civilian and military applications for applications such as underground mining, nuclear plant operations, planetary exploration, intelligence, surveillance and reconnaissance (ISR) missions and manned-unmanned teaming. We consider a multi-objective, multiple-vehicle routing problem in which teams of manned ground vehicles (MGVs) and AMRs are deployed respectively in a leader-follower framework to execute missions with differing requirements for MGVs and AMRs while considering human-robot interactions (HRI). HRI studies highlight the costs of managing a team of follower AMRs by a leader MGV. This paper aims to compute feasible visit sequences, replenishments, team compositions and number of MGV-AMR teams deployed such that the requirements for MGVs and AMRs for the missions are met and the routing, replenishment, HRI and team deployment costs are at minimum. The problem is first modeled as a mixed-integer linear program (MILP) that can be solved to optimality by off-the-shelf commercial solvers for small-sized instances. For larger instances, a variable neighborhood search algorithm is offered to compute near optimal solutions and address the challenges that arise when solving the combinatorial multi-objective routing optimization problem. Finally, computational experiments that corroborate the effectiveness of the proposed algorithms are presented.

Index Terms—Unmanned autonomous vehicles, human-robot interaction, vehicle routing, variable neighborhood search, multi-objective optimization.

I. INTRODUCTION

INDUSTRY 4.0 [1] concepts and technologies such as artificial intelligence (AI), machine learning, cloud computing are establishing their presence across innumerable fields in the recent years. Advancements in these technologies is causing a paradigm shift in the way autonomous vehicle technology is applied across various civilian and military applications. Unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) previously controlled manually or remotely, with the incorporation of industry 4.0 technologies are able to operate with increasing autonomy giving rise to AMRs. AMR is a type of robot that uses sophisticated sensors, AI, machine learning etc. to understand and maneuver through its environment independently [2].

The use of AMRs to assist humans can be seen across various civilian industries such as warehousing, healthcare, nuclear plant operations, environmental monitoring, and military applications such as explosive ordnance disposal (EOD), firefighting, search and rescue. Ford Motors, Spain, is using AMRs to transport spare parts for production equipment from the warehouse to the production lines [3]. AMR running on intel technology is being used in a hospital in Mexico to triage COVID-19 patients. [4]. Mining companies such as Caterpillar Global Mining, ASI Mining are employing autonomous mining trucks in open-pit mines. Authors in [5] develop a trajectory planning framework for autonomous mining trucks operated in open-pit mines. In 2017, the United States Army published its strategy for the development and deployment of robotic and autonomous systems [6] emphasizing primarily on human-machine collaboration by integrating army with robotic and autonomous systems solutions. Given the numerous applications of AMRs and human-robot teaming, there is a need for efficiently modeling AMR path planning problems.

AMR path planning problems can be broadly classified into high and low level path planning algorithms. Low level ‘path planning algorithms’ solve the challenge of finding an optimal trajectory between a pair of source and destination while considering obstacles, and provide closed-loop control signals to each vehicle so that they can follow the trajectory with minimum deviations [7], [8]. Authors in [9], alongside multiple autonomous underwater vehicle low level path planning, perform task assignment to reasonably assign AUVs to targets. Authors in [10] propose a multi-agent pick up and delivery framework to efficiently allocate tasks and find paths for hybrid swarms consisting of human workers and automated guided vehicles considering uncertainties of human behavior and the dynamic changes of tasks into account. A high-level ‘mission planning algorithm’ provides the sequence of visits for the vehicle while considering points of interests (POI), environment uncertainties, and other operational constraints. In this research, we consider a high level, multi objective, multiple vehicle routing problem (MVRP)
in which MGV-AMR teams are deployed in a leader-follower framework to implement missions requiring human-robot collaboration. The problem considered in this research differs from general high-level ‘mission planning algorithm’ (multi vehicle routing problems - VRPs) in that, in addition to finding optimal sequence of visits to POIs, the problem also optimizes the team compositions of the MGV-AMR teams considering HRI. The optimal team compositions of the MGV-AMR teams are modeled as a generalized assignment problem (GAP). Both VRP and GAP are combinatorial and NP-Hard problems that are challenging to solve.

MGV-AMR teams in a leader-follower framework are deployed in semi-autonomous applications. Within the leader-follower framework, the leader refers to an MGV. The MGV leader lays down “virtual train tracks” which a set of follower AMRs use to follow the leader. Determining ideal team compositions, i.e., the ratio of human operators to robots is crucial for missions involving MGV-AMR teams [11]. The team compositions used in this effort are based on HRI studies. The ideal team compositions for MGV-AMR teams are derived from various characteristics such as neglect tolerance and activity time. The autonomy of a robot is measured by its neglect time. A human operator can ignore a robot for the duration of its neglect time. Activity time measures the amount of time a human operator is involved in instructing a robot [12]. These HRI studies provide a model for the human costs of managing a team of AMRs by MGVs. Authors in [13] conducted an urban search and rescue mission (USAR) to evaluate the task performance while a human operator was carrying varying number of robots. Fig. 1 explains the HRI/team composition costs based on [13]. Authors in [12] also measure task effectiveness as a function of the number of robots carried by a human operator.

A detailed description of high level, multi objective, multiple vehicle routing problem (MVRP) considered in this research, where MGV-AMR teams, more specifically MGV-UGV teams are deployed in a leader-follower framework to implement missions requiring human-robot collaboration follows. Given a set of POIs with differing requirements for MGVs and UGVs, the objective is to find ideal number of teams, sequence of visits and replenishments for each team, and team compositions such that the following conditions are satisfied:

1) The demand for the MGVs and UGVs at the POIs are satisfied. The demand for the UGVs is met either by the MGV-UGV team travelling to the POIs or by a combination of the former and additional replenishments supplied to the POI from the depot that then join the MGV-UGV team at the POI.

2) The MGV-UGV teams follow a leader-follower framework where follower UGVs follow a leader MGV based on HRI studies with an exception for the replenishment UGVs supplied from the depot until they join the MGV-UGV team at a POI.

3) Sum of travel (routing and replenishment) costs, HRI (team composition) costs and costs for the number of teams deployed to complete the missions are minimum.

Given two vehicles, seven POIs and the demand for UGVs at POIs indicated in Fig. 2(a), a feasible solution for the high level MVRP instance is shown in Fig. 2(b). In the next section, we present a detailed overview of the literature that concerns this problem.

II. RELATED WORK

The MVRP described in this paper is a combination of the capacitated vehicle routing problem (CVRP) [14] and the generalized assignment problem (GAP) [15]. The CVRP problem determines the optimal routes for the MGV-AMR teams and the GAP problem is used to determine the optimal team compositions for each team; in this case, the costs for the team compositions are based on HRI studies.

The CVRP is a variant of the vehicle routing problem (VRP) [16] which determines the optimal routes for a fleet of capacitated vehicles initially located at one or more depots to serve a set of customers [17]. There has been extensive research conducted in literature to apply exact methods [18], [19] that find the optimal solution to the CVRP using methods such as branch-and-cut. Heuristics [20], [21] that solve the problem faster and
efficiently, however compromising on optimality, have also been explored. Given \( n \) agents and \( m \) tasks, the GAP determines optimal allocation of agents to tasks, such that agents execute only one task subject to capacity restrictions [15]. Similar to the CVRP, there is extensive research on exact methods [22], [23] and heuristics [24], [25] for GAP.

In our earlier work presented in [26], we propose an optimization model to solve the high level, multi objective MVRP problem. Although there has been extensive research to solve low level path planning problems [5], [7], and high level mission planning algorithms (VRPs and variants), to the best of our knowledge, this was a first attempt at proposing a solution to the high level multi-vehicle route planning problems involving MGV-AMR teams taking human-robot interaction into consideration. The optimization model is presented in this paper in Section III to keep the presentation self-contained. The CVRP problem and the GAP problem, the two key sub-problems of the MVRP, are NP-Hard [27]. Therefore, scaling the optimization model to solve large scale instances is very challenging, time consuming and computationally expensive. Hence, the use of heuristic methods becomes inexcusable.

VNS, proposed by Mladenovic and Hansen [28], is a very well-known metaheuristic used to solve such NP-hard optimization problems. VNS utilizes systematic change of neighborhoods within a local search algorithm exploring increasingly distant neighborhoods of the current incumbent solution and moving to a new solution only if an improvement is made [29]. Authors in [30] apply an augmented VNS approach, to solve a precedence constrained colored traveling salesman problem where operations or activities may be constrained by some precedence relationships and colors are used to distinguish the accessibility of individual cities to salesmen. They show that their approach outperforms, two genetic algorithms, three other VNS variants and LKH-3 [31] in most cases. Authors in [32] apply VNS to multi-depot vehicle routing problem with time windows for instances containing up to 300 customers. They conclude that VNS is able to perform better with solution quality and scaling in comparison with Tabu-search heuristic [33]. VNS has also been an efficient heuristic for assignment problems [34], [35]. Adaptation of VNS to multi-objective combinatorial optimization problems is gaining pace in the research community. Authors in [36] suggest an adapted VNS approach to solve two combinatorial bi-objective optimization problems. They report that the suggested approach outperforms both Non-dominated Sorting Genetic Algorithm (NGSA) and the Strength Pareto Evolutionary Algorithm, two standard algorithms used multi-objective optimization. Authors in [37] apply the multi-objective VNS to a path planning problem in mobile robotics by optimizing three objectives, namely path safety to avoid obstacles, path length to control robot operation time and path smoothness to optimize energy consumption to obtain accurate and efficient paths. They conclude that the multi objective VNS approach is superior in comparison to the NSGA. Given the efficacy of VNS in solving various classes of vehicle routing problems including problem with multiple vehicles, multiple depots, time windows, capacity restrictions and multi objective combinatorial optimization problems, in this research, we propose the variable neighborhood search (VNS) algorithm approach to the MVRP problem and address the challenge of scaling the approach to large test instances.

The remainder of the paper is organized as follows. The optimization model used to solve the high-level MVRP is presented in Section III. The variable neighborhood search algorithm and approach are presented in Section IV. Computational results for randomly generated instances are presented in Section V. Finally, the paper concludes in Section VI.

III. OPTIMIZATION MODEL

The optimization model presented in our previous work in [26] is included in this section with additional explanation for completeness.

A. Problem Description

Given a set of POIs with differing requirements MGVs and AMRs (specifically UGVs) at each POI, the high level, multi objective, MVRP model seeks to find the ideal number of leader-follower MGV-UGV teams to be deployed, the team compositions for each MGV-UGV team considering HRI studies, the replenishment UGVs required to satisfy the demand at the POIs and the sequence of POI visits of each MGV-UGV team such that the missions are completed efficiently.

B. Notation

Let \( d_0 \) denote the depot where \( K \) different categories of heterogeneous MGVs and UGVs represented as \( M_k, m \in M_k \), are initially stationed. Let \( P = \{p_1, \ldots, p_l\} \) denotes the set of POIs. POIs are the locations at which MGV-UGV teams are required to execute missions requiring human-robot collaboration. \( V = P \cup d_0 \) denotes the set of vertices and \( E \) denotes the set of edges joining any pair of vertices.

For each edge \( (i, j) \in E \), \( c_{ij} \) represents the travel cost incurred while traversing the edge \( (i, j) \). Parameter \( h_n \) represents the HRI costs of managing ‘n’ UGVs and set \( N \) (indexed by \( n \)) is used to represent the number of UGVs in a team. Parameter \( T \) represents the cost incurred for each MGV-UGV team deployed to execute the missions.

For any set \( S \subset V \), \( \delta^+(S) = \{(i, j) \in E : i \in S, j \notin S \} \) and \( \delta^-(S) = \{(i, j) \in E : i \notin S, j \in S \} \) denote the set of outgoing and incoming edges from the set \( S \). When \( S = \{i\} \), we shall simply write \( \delta^+(i) \) and \( \delta^-(i) \) instead of \( \delta^+\{i\} \) and \( \delta^-\{i\} \), respectively. Also, for any \( A \subseteq E \), let \( x(A) = \sum_{(i,j) \in A} x_{ij} \).

C. Decision Variables

The decision variables for the MVRP are as follows: each edge \((i, j) \in E\) is associated with a variable \( x_{ij}^m \) that equals 1 if the edge \((i, j)\) is traversed by the \( m^{th} \) MGV, and 0 otherwise. Variable \( y_{ij}^m \) represents the number of UGVs visiting the POI \( j \in P \) along with the MGV \( m \). Variable \( \tilde{y}_{ij}^m \) represents variable \( y_{ij}^m \) as a series of binary variables. Variable \( z_{ij}^m \) represents the number of UGV’s provided as reinforcement to the POI \( j \in P \) from the base depot \( d_0 \) for the MGV \( m \). Variable \( r_{ij}^m \) represents variable \( z_{ij}^m \) as a series of binary variables. Also, variable \( w_{ij}^m \) represents the number of UGVs that visit a POI \( i \) then a POI \( j \), where \( i, j \in P \) along with the MGV \( m \).
D. Objective Function

The objective of the problem is to minimize the sum of (1) routing costs, (2) replenishment costs, (3) HRI costs and finally (4) the cost incurred by the teams to the mission. The expressions for each of these costs functions are as follows:

Routing costs: $R^1 \triangleq \sum_{(i,j) \in E, n \in N} c_{ij} x^m_{ij}$\tag{1a}

Replenishment costs: $R^2 \triangleq \sum_{(i,j) \in E, n \in N} c_{dij} r^m_{nj}$\tag{1b}

HRI costs: $\mathcal{H} \triangleq \sum_{j \in V, n \in N} h_n y^m_{nj}$\tag{1c}

Team costs: $\mathcal{T} \triangleq \sum_{j \in \bar{V}} T \cdot x^m_{0j}$\tag{1d}

The objective function is the sum of the of above costs weighted by user provided parameters $\alpha$, $\beta$, and $\gamma$ as follows:

$$\min \alpha \cdot (R^1 + R^2) + \beta \cdot \mathcal{H} + \gamma \cdot \mathcal{T}$$\tag{2}

The weighted sum method is a classical approach used to solve multi-objective optimization problems. The optimal solution to the problem depends on the weights assigned to the objectives. Weights are assigned to the objective in proportion to the preference factor assigned to the objective [38]. Alternatively, a problem instance can be evaluated for different weights to give decision makers multiple perspectives.

E. Routing Constraints

Routing constraints impose the requirements that all POIs $i \in P$ should be visited and that the demand for each MGV and UGV at the POIs is satisfied. Constraint (3a) ensures that a feasible solution is connected and are referred to as sub tour elimination constraints. The optimization problem is initially solved by relaxing these constraints. Once a feasible solution is obtained, the callback feature offered by solvers such as CPLEX, Gurobi etc. are used to add the constraints to the model if the constraints in (3a) are violated. A constraint is said to be in violation if the tour does not contain the depot $d_0$. Constraint (3b) states that the number of MGV-UGV teams leaving the depot must come back to the depot after completing the missions at the visited POIs. Constraint (3c) states that and MGV-UGV team entering a POI must leave the POI. For each POI $i$, the pair of constraints in (3d) and (3e) state that the demand for MGVs and UGVs at POI $i$ are satisfied.

$$x^m(S) \leq |S| - 1 \quad \forall (i,j) \in S,$$
$$S \subset V \setminus \{d_0\} : S \neq \emptyset, \quad \forall m \in M_k, k \in K,$$\tag{3a}

$$x^m(\delta^+(d_0)) = x^m(\delta^-(d_0)) \quad \forall m \in M_k, k \in K,$$\tag{3b}

$$x^m(\delta^+(i)) = x^m(\delta^-(i)) \quad \forall i \in P, m \in M_k, k \in K,$$\tag{3c}

$$\sum_{m \in M_k} x^m(\delta^+(i)) \geq a_{ik} \text{ and},$$

$$\sum_{m \in M_k} x^m(\delta^-(i)) \geq a_{ik} \quad \forall i \in P, k \in K,$$\tag{3d}

$$\sum_{m \in M_k} y^m_j \geq b_{jk} \quad \forall j \in P, k \in K,$$\tag{3e}

F. HRI/Teaming Constraints

The teaming constraints decide the team sizes for the MGV-UGV teams. For each POI, constraint (4a) states that the number of UGVs along side MGV $m$ visiting the POI should be equal to the the incoming UGV’s from the previously visited POI and the reinforcement provided to the current POI from the base depot. Constraints in (4b)–(4d) state that UGVs’ travel alongside MGV $m$ if and only if the edge $x^m_{ij}$ is traversed. These constraints are used to account for the non-linear relationship ($\sum_{m \in M_k} w_{ij}^m = \sum_{m \in M_k} y_{ij}^m$ only if $x^m_{ij} = 1$) to a linear one. Constraint (4e) state the dependence of UGVs on an MGV following a leader-follower framework, and constraints (4f) define the capacity for UGVs. Constraints (4g) state that team size does not change for each manned GV $m$, and the constraints (4h) are the special order sets of constraints (type 1) stating that only one binary variable can be chosen. Constraint (4i) is used to account for replenishment costs at each POI. Finally, constraint (4j) imposes restrictions on the decision variables.

$$\sum_{m \in M_k, v \in P, d_0} w_{ij}^m + z_{j}^m = \sum_{m \in M_k} y_{ij}^m \quad \forall j \in (P, d_0)$$\tag{4a}

$$\sum_{m \in M_k} w_{ij}^m \leq \sum_{m \in M_k} B \cdot x^m_{ij},$$
$$\forall i \in (P, d_0), \forall j \in (P, d_0), k \in K,$$\tag{4b}

$$\sum_{m \in M_k} w_{ij}^m \leq \sum_{m \in M_k} y_{ij}^m,$$
$$\forall j \in (P, d_0), \forall i \in (P, d_0), k \in K,$$\tag{4c}

$$\sum_{m \in M_k} w_{ij}^m \geq \sum_{m \in M_k} (y_{ij}^m - (1 - x^m_{ij}) \cdot B),$$
$$\forall i \in (P, d_0), \forall j \in (P, d_0), k \in K,$$\tag{4d}

$$0 \leq y_{ij}^m \leq \ell_k x^m_{ij} \quad \forall (i,j) \in E, m \in M_k, k \in K,$$\tag{4e}

$$0 \leq \sum_{m \in M_k} y_{ij}^m \leq \ell_k \quad \forall k \in K,$$\tag{4f}

$$y_{ij}^m = \sum_{n \in N} n_{ij} y_{nij}^m \quad \forall j \in P, m \in M_k, k \in K,$$\tag{4g}

$$\sum_{n \in N} y_{nij}^m \leq 1 \quad \forall m \in M_k, k \in K,$$\tag{4h}

$$z_{ij}^m = \sum_{n \in N} n_{ij} r_{nij}^m \quad \forall j \in P, m \in M_k, k \in K,$$\tag{4i}

$$x^m_{ij} \in \{0, 1\}, y_{ij}^m \in \mathbb{Z}^+, w_{ij}^m \in \mathbb{Z}^+, z_{ij}^m \in \mathbb{Z}^+, y_{nij}^m \in \{0, 1\}, 0 \leq s_{ij}^m \leq 1,$$

$$\forall (i,j) \in E, n \in N, m \in M_k, k \in K.$$\tag{4j}
The optimization model proposed to solve the MVRP contains the CVRP and GAP, both of which individually are combinatorial optimization problems. They are NP-Hard [27]. Therefore, the optimization model also is combinatorial. The model can find optimal solution to small instances, the results of which are presented in [26]. Scaling the optimization model to larger instances is computationally challenging. In the next section, we present the variable neighborhood search algorithm to address this challenge and compute high quality sub-optimal solutions for the MVRP.

IV. VARIABLE NEIGHBORHOOD SEARCH

The skewed variable neighborhood search algorithm (SVNS) is a variant of the VNS meta-heuristic that allows for the exploration of valleys far from the incumbent solution [28]. The exploration of far away valleys is done by allowing for ‘recentering’ of the search. A solution outside of the incumbent solution is accepted if it lies far away from the incumbent solution. Recentering requires a metric to define the distance between the incumbent and current solutions. In this research, we use the SVNS, a variant of VNS.

A. Construction Heuristic

SVNS starts with an initial feasible solution. Hence, we develop an initial feasible solution to the MVRP. Construction heuristic start with an empty solution to a given problem and extend the current solution repeatedly until a complete solution is found [39]. The initial feasible solution to the MVRP consists of two components: feasible routes i.e., the sequence of visits to the POIs by MGV-UGV teams such that all POIs are visited and feasible assignments i.e., the team compositions for MGV-UGV teams for each route. Feasible assignments ensure that the demand for the UGVs at the POI is met either by the incoming team to the POI from the previously visited POI or by the replenishment UGVs supplied from the base depot. We first construct the initial routes to the multiple travelling salesman problem (mTSP) by using an extension of the Lin-Kernighan-Helsgaun heuristic [40], LKH-3 heuristic solver [31]. We then construct feasible assignments to the MVRP by comparing the following two assignment strategies and implementing the strategy that provides a better solution:

1) asgn-rule1: For each MGV-UGV team visiting a subset of POIs, consider the maximum UGV demand from the subset and provide this UGV demand from the depot allowing for no replenishments from the depot.

2) asgn-rule2: For each MGV-UGV team visiting a subset of POIs, provide required UGV demand and replenish POIs as and when required based on the UGV demand at POIs.

The choice of assignment strategy implemented in the solution is dependent on the weights $\alpha$ and $\beta$ used in the objective function for the MVRP problem. asgn-rule1 strategy would provide a better solution when weight $\alpha$ is prioritized over $\beta$, since no replenishments are allowed leading to a replenishment cost of 0, however, increasing the HRI cost due to the increase in team sizes. Alternatively, asgn-rule2 increases the replenishment costs thereby reducing the team sizes and the HRI costs proving effective when weight $\beta$ is prioritized over $\alpha$. Fig. 3 explains the assignment strategies. Finally, we reverse the routes generated by the LHK-3 solver and construct feasible assignments once again as mentioned above. The best solution overall is used as the initial feasible solution for the SVNS. The costs for the construction heuristic solution may be high since the routes obtained from the LKH-3 heuristic may not be the best with respect to the assignments of the MGV-UGV teams. A different sequence of routes may yield a better suited solution for assignments. In the next section, we define the neighborhoods used in SVNS.

B. Neighborhoods

We define seven neighborhoods for the MVRP, three intra route neighborhoods, namely (i) reverse, (ii) POI-swap-intra, (iii) 2-opt-intra and three inter route neighborhoods, namely (iv) POI-remove-insert, (v) POI-swap-inter and (vi) POI-SequenceExchange-inter. Given routes for the MGV-UGV teams, the reverse neighborhood reverses the sequence of visits to POIs for each route. The POI-swap-intra neighborhood selects randomly, two POIs from a route and interchanges them with each other. 2-opt was first introduced by Croes [41]. The 2-opt-intra neighborhood makes use of the 2-opt swap mechanism where, given a route and a segment of the route, the segment is reversed and reinserted back in its place. The intra neighborhoods are explained in Fig. 4. Given two routes, the POI-remove-insert takes a POI randomly from one route and inserts it into a random position in another route. The POI-swap-inter neighborhood takes a POI at random from two routes and exchanges the POIs. Finally, the POI-SequenceExchange-inter neighborhood takes one segment each, from two routes and exchanges the segments. The inter route neighborhoods are explained in Fig. 5. For assignments, all intra route and inter route neighborhoods are evaluated with the two assignment strategies mentioned in Section IV-A and the best solution is used.
and the new SVNS heuristic to in the total cost if is large enough provided the distance between and is large enough [42]. Given two feasible solutions where a solution represents the total cost for the MVRP, a solution is said to be better than if the total cost is strictly less than since the MVRP is a cost minimization problem. Solution is said to be worse than if the total cost is strictly greater than . The distance metric for the MVRP is defined as the relative gap (%) in the total cost of the two solutions. Given two feasible solutions, and , the distance between them is said to be large enough if the relative gap is greater than or equal to 20% and less than or equal to 50%. If the search is recentered, a parameter is initialized to 1, otherwise, the parameter is increased by 1 unit. Only when the total objective value decreases, the number of iterations with no improvement (UnImproved) is initialized to 0. In all the other cases, UnImproved is increased by 1. The pseudo-code of the SVNS is presented in Algorithm 1.

V. COMPUTATIONAL RESULTS

The SVNS algorithm for the MVRP is implemented using Python. All the computational experiments were run on an Intel(R) Core(TM) i5-6200 U PC running at 2.30 GHz and 4 GB RAM.

A. Performance of SVNS Algorithm

To show the overall performance and effectiveness of the algorithm, we generate three sets of instances: 80 small scale instances with five POIs and two vehicles; 80 medium scale instances with 20 POIs, three and five vehicles; and 80 large scale instances with 40 POIs, six and eight vehicles. For each of these instances, the path traversal costs and the replenishment costs are measured as the Euclidean distance costs for the edges. The edge for replenishment cost is the edge connecting the depot to the POI where replenishment is supplied. The HRI (team compositions) are based on HRI studies. We choose HRI costs based on Fig. 1. The costs for the number of teams deployed linearly increases as the number of vehicles deployed for the missions increase. The demand for the UGVs is uniformly distributed between one and 12 at the POIs. The total capacity for UGVs that can be carried by an MGV is 12. The weights for the objective function , , and can take values 0, 0.1, 0.3, 0.6, 1 such that the that the sum of weights adds up to one.

The small scale instance runs are made for both the optimization model presented in Section III and the SVNS heuristic to evaluate the performance of SVNS. The average run time for

Additionally, we define an assignment neighborhood named (vii) asgn-rule3 as follows: Given a MGV-UGV team visiting a set of POIs, the asgn-rule3 neighborhood meets the UGV demand at the POIs by allowing replenishments only at a few selected POIs. For POIs where no replenishments are allowed the UGV demand is carried from the MGV-UGV team coming into the POI. This neighborhood allows for a balance of the replenishments and team sizes (replenishment and HRI costs) for the MVRP, in contrast to the two assignment strategy asgn-rule1 and asgn-rule2 in Section IV-A.

C. Algorithm

The construction heuristic solution obtained in Section IV-A is given as the initial feasible solution to SVNS. The SVNS algorithm consists of three steps: (i) shaking, (ii) local search, and (iii) recentering. The POI-swap-intra neighborhood presented in Section IV-B is used in the shaking phase of the algorithm. The shaking phase is used to escape from the incumbent solution. The 2-opt-intra neighborhood, all three inter route neighborhoods and the asgn-rule3 neighborhood are used in local search phase of the algorithm. The recentering step of the algorithm performs the following: if the solution from the shaking and local search phase is better than the incumbent solution computed thus far, the search is recentered i.e., is assigned to and the new solution becomes the incumbent solution. This is done in line 15 of the SVNS algorithm. Additionally in the SVNS, line 23 of the algorithm, the search is also recentered when is worse than , provided the distance between and is large enough [42].

Fig. 4. (a) Shows the locations of the depot and POIs and path for a MGV-UGV team before applying intra neighborhood moves, (b) Shows path after applying reverse neighborhood, (c) Shows path after applying POI-swap-intra neighborhood, and (d) Shows path after applying 2-opt-intra neighborhood.

Fig. 5. (a) Shows the locations of the depot and POIs and paths for two MGV-UGV teams before applying inter neighborhood moves, (b) Shows paths after applying POI-remove-insert neighborhood, (c) Shows paths after applying POI-swap-inter neighborhood, and (d) Shows paths after applying POI-SequenceExchange-inter neighborhood.
Algorithm 1: Skewed Variable Neighborhood Search.

**Input:** $N_j$ for Shaking phase: POI-swap-intra
$N_j$ for Local Search Phase: 2-opt-intra, POI-remove-insert, POI-swap-inter, POI-SequenceExchange-inter, asgn-rule3

1. $f \leftarrow$ construction heuristic solution.
2. **while** UnImproved $<$ UnImproved\_max **do**
3.     $k \leftarrow 0$
4.     **while** $k < k\_max$ **do**
5.         $f' \leftarrow \text{Shake}(f)$ ▷Shake
6.         $j \leftarrow 0$
7.         **while** $j < 5$ **do** ▷Local Search
8.             Find best neighbor in $N_j(f') \rightarrow f''$
9.             **if** $f''$ is better than $f'$ **then**
10.                $f' = f''$
11.                $j \leftarrow 0$
12.             **else**
13.                 $j \leftarrow j + 1$
14.             $f'' = f'$$\uparrow$Recenter
15.             **if** $f''$ is better than $f$ **then**
16.                 $f = f''$
17.                 $k \leftarrow 0$
18.             **else**
19.                 UnImproved $\leftarrow 0$
20.             **if** $f$ is better than IncumbentSol **then**
21.                 IncumbentSol $\leftarrow x$
22.             **else**
23.                 UnImproved $\leftarrow$ UnImproved + 1
24.             **if** $f''$ is worse than and far from $f$ **then**
25.                 $f = f''$
26.             **else**
27.                 $k \leftarrow k + 1$

**Output:** IncumbentSol

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small scale instances for the optimization model and SVNS are 4.28 and 2.02 seconds, respectively. SVNS results in optimal solutions for all 80 small scale instances. The initial feasible solution given by the construction heuristic in Section IV-A alone produces optimal solutions for 38 instances of the 80 small scale instances. For the remaining 42 instances, the SVNS improves the initial feasible solution provided by the construction heuristic by a maximum of 36.35% and an average improvement of 11.17%. For the remainder of the paper, given 2 MVRP objective function costs, $f'$ and $f''$, improvement is defined as the decrease from $f'$ to $f''$ as a percentage of $f'$. Fig. 6(a) summarizes the performance of the SVNS algorithm for the remaining 42 small scale instances.

The optimization model due to being combinatorial in nature did not scale to find optimal solutions for medium and large scale instances. However with SVNS, medium scale instances take an average time of 11.6 seconds and 1.32 minutes for instances with three and five vehicles, respectively, and large scale instances take an average time of 5.79 and 13.21 minutes for instances with six and eight vehicles, respectively, to obtain sub-optimal solutions. SVNS improves the quality of the initial feasible solution by a maximum of 25.51% for 56 of the 80 medium scale instances and a maximum of 57.34% and an average of 25.48% for 35 of the 80 large scale instances. Fig. 6(b) and (c) summarize the performance of the SVNS algorithm for SVNS improved medium and large scale instances.

**B. Parametric Analysis**

Parameters, UnImproved\_max and $k\_max$ are used in line 2 and 4 respectively in the SVNS algorithm presented in Algorithm 1. We generate 30 random instances with 10 small, 10 medium and 10 large scale instances to test the SVNS algorithm for different values of parameters, UnImproved\_max and $k\_max$. Fig. 7 summarizes the average improvement in
the MVRP cost from the construction heuristic using SVNS for differing values of the two parameters. The average improvement increases as the values of the parameters are increased. The lowest average improvement of 35.55% occurs when both parameters UnImproved_max and $k_{\text{max}}$ are set to a value of 10. The average improvements are comparable when UnImproved_max and $k_{\text{max}}$ are set to 40 and 30 with 40.45% (case 1) and 40 and 60 with 40.76% (case 2) respectively. The time taken by SVNS increases by 4.01% for the 10 large scale instances between case 1 and case 2. Based on the results, we set the parameter values of UnImproved_max to 40 and $k_{\text{max}}$ to 30. Increasing the values may yield better solutions, however, compromising on the time taken to solve the instances.

C. Neighborhood Study

Fig. 8 summarizes the number of instances that result in optimal solution for small scale instances when SVNS algorithm is used with one neighborhood in the local search phase at a time. SVNS with POI-swap-inter and POI-SequenceExchange-inter neighborhoods result in optimal solutions for 65 of the 80 small scale instances. The POI-remove-insert results in optimal solutions for 64 instances. All 3 neighborhoods are inter route neighborhoods and perform comparatively. They are also better in comparison to the 2-opt-intra, intra route neighborhood. The performance of the SVNS algorithm for small, medium and large scale instances for each neighborhood operator used in the local search phase of the algorithm is summarized in Table I. The POI-remove-insert neighborhood gives the highest average improvement for small and large scale instances. For medium scale instances, the highest average improvement is observed with the POI-swap-inter neighborhood. The performance of all three inter route neighborhoods: POI-remove-insert, and POI-SequenceExchange-Inter used in the local search of the SVNS are nearly identical. All the inter route neighborhoods perform better than the 2-opt-intra route neighborhood with small, medium and large scale instances. Overall, results suggest that the inter route neighborhoods in the local search phase of the SVNS show superior performance when compared to intra route neighborhood. The performance of the asgn-rule3 neighborhood improves as the instance size increases. However, the average improvement seen in asgn-rule3 neighborhood remains low as the neighborhood does not perform any route modifications.

D. Sensitivity of Weights on Multi-Objective Function

The weights for the objective function to the MVRP, given by $\alpha$, $\beta$, and $\gamma$ can either be predetermined by the decision makers to find the best solution based on the priority given to each of the objectives or pareto solutions obtained by differing the weights can be offered to the decision makers. In multi objective optimization (MOO), a solution is said to be non dominated, pareto optimal if none of the objective functions can be improved in value without degrading some of the other objective values [43]. The weighted sum method is a classical A priori method used to solve MOO problems. The set of objectives are scalarized to give a single objective by adding weights to each of the objectives. The weights $\alpha$, $\beta$, and $\gamma$ are parameters for scalarization.

Fig. 9 plots the travel (path + replenishment) costs vs the HRI costs for differing weights $\alpha$ and $\beta$ for five small scale instances (ss1, ss2, ss3, ss4 and ss5) to observe the effect of weights on the overall MVRP solution.
TABLE I
SVNS IMPROVEMENT OF MVRP COST FROM CONSTRUCTION HEURISTIC COST WITH INDIVIDUAL NEIGHBORHOODS IN LOCAL SEARCH PHASE FOR SMALL, MEDIUM AND LARGE SCALE INSTANCES

| Instance set | Neighborhood | Number of instances improved (Total instances: 80) | Maximum improvement (%) | Average improvement (%) |
|-------------|--------------|---------------------------------------------------|-------------------------|-------------------------|
| Small scale | 2-opt-intra  | 13                                                | 28.56                   | 10.79                   |
|             | POI-remove-insert | 37                                              | 31.81                   | 11.73                   |
|             | POI-swap-inter  | 37                                               | 35.35                   | 11.27                   |
|             | POI-SequenceExchange-inter | 37                                           | 35.35                   | 11.27                   |
|             | agn-rule3  | 14                                                | 28.56                   | 9.77                    |
| Medium scale | 2-opt-intra  | 45                                                | 51.51                   | 21.53                   |
|             | POI-remove-insert | 48                                              | 59.84                   | 26.22                   |
|             | POI-swap-inter  | 47                                               | 59.84                   | 27.28                   |
|             | POI-SequenceExchange-inter | 50                                           | 61.35                   | 24.39                   |
|             | agn-rule3  | 46                                                | 49.22                   | 19.53                   |
| Large scale | 2-opt-intra  | 31                                                | 43.74                   | 18.77                   |
|             | POI-remove-insert | 31                                              | 54.15                   | 25.14                   |
|             | POI-swap-inter  | 31                                               | 55.66                   | 24.44                   |
|             | POI-SequenceExchange-inter | 30                                           | 54.89                   | 24.78                   |
|             | agn-rule3  | 32                                                | 41.65                   | 18.21                   |

TABLE II
SOLUTIONS FOR PROBLEM INSTANCES WITH DIFFERING WEIGHTS (α, β, γ)

| Instance | User Parameters | Path Costs | Travel Costs | Replenishment Costs | HRI Costs | Total Cost | Run Time (sec) | SVNS vs opt |
|----------|-----------------|------------|--------------|---------------------|-----------|------------|---------------|-------------|
| ss1      | α 0.1 0.1 0.1   | 521.89     | 0            | 250.00              | 871.89    | 1.43       | 6             |            |
|          | β 0.3 0.1 0.1   | 352.89     | 0            | 250.00              | 871.89    | 1.43       | 6             |            |
|          | γ 0.3 0.1 0.1   | 521.89     | 0            | 250.00              | 871.89    | 1.43       | 6             |            |
|          | ss2             | 226.30     | 0            | 190.30              | 553.14    | 0.95       | 7             |            |
|          | ss3             | 422.71     | 83.34        | 160.30              | 766.08    | 1.47       | 6             |            |
|          | ss4             | 420.82     | 0            | 250.00              | 770.82    | 1.27       | 5             |            |
|          | ss5             | 420.82     | 0            | 250.00              | 770.82    | 2.47       | 5             |            |
|          | ss6             | 422.71     | 83.34        | 160.30              | 766.08    | 1.31       | 4             |            |
|          | ss7             | 420.82     | 0            | 250.00              | 770.82    | 1.27       | 5             |            |

Cost in Table II to account for the team cost for deploying two vehicles. It can be observed that the travel costs (path and replenishments costs) are lesser when weight α is prioritized over β. This can be particularly advantageous when MGV-UGV teams are maneuvering through unfamiliar and difficult terrains and providing replenishments in such a scenario would be unsuitable and expensive. However, this increases the team sizes for the MGV-UGV teams, thereby increasing HRI/team composition costs. Alternatively, weight β can be prioritized to reduce load on the MGVs and reduce HRI costs. However, such scenarios will have higher travel costs as observed. The best course of action for a given problem instance can be implemented based on the interests of the decision makers by studying the solution characteristics for the instance.

VI. CONCLUSION

In this research, we propose the SVNS algorithm to the high level multi-objective mission planning problem with multiple vehicles considering human robot interactions. Specifically, MGV-AMR teams are deployed in a leader-follower (MGV leader - AMR followers) framework to execute missions at POIs with differing requirements for MGVs and AMRs. To the best of our knowledge, our previous work in [26] was a first attempt to model a vehicle routing problem taking human robot interaction into consideration. The model developed is a combinatorial optimization problem and is NP-Hard. SVNS is a variant of the VNS meta-heuristic that enhances the exploration of far away valleys. The SVNS addresses the challenges faced in scaling the previously modelled combinatorial optimization problem for the MVRP in [26]. We generate three sets of instances: small, medium and large scale to evaluate the performance of SVNS. The SVNS produces optimal solutions for all small scale instances. For medium and large scale instances, SVNS generates high quality sub-optimal solutions for the optimization problem for more realistic and practical scenarios in reasonable time. Our future work involves focusing on extending the model to include uncertainties in the availability of UGVs, travel time, etc. Additional functionalities such as vehicle refueling can be incorporated into the model. Machine learning algorithms can be used to find the appropriate values for the weights, α, β, and γ used in the objective function.
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