

Examining teleoperation as a deadlock resolution strategy for autonomous mobile robots

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Teleoperation is typically used as a fallback mechanism, rather than a formal deadlock resolution strategy. As such, the performance metrics used to evaluate deadlock resolution strategies are not measured during teleoperation, which does not allow us to compare the effectiveness of teleoperation relative to other strategies. This study aims to fill this research gap by identifying the common performance metrics between current deadlock resolution strategies and the teleoperation strategy.

[Keywords: teleoperation, deadlock resolution, performance metrics, autonomous mobile robots]

1 INTRODUCTION

1.1 DEFINITION FOR AUTONOMOUS MOBILE ROBOTS

An autonomous mobile robot (AMR) is a system that operates in an unpredictable and partially unknown environment. This means the robot must have the ability to navigate without disruption, avoiding obstacles placed within its operational environment, without human intervention [1].

AMRs are deployed across a broad spectrum of industries varying from agriculture, healthcare, manufacturing to logistics and warehousing.

1.2 DEADLOCK DEFINITION IN THE CONTEXT OF AMRS

A deadlock is a circular wait condition which occurs when two or more robots prevent each other from reaching their respective goal; meaning each robot holds a shared resource, like a narrow lane, intersection or charging dock, while waiting for another resource held by the next robot.

Deadlock prevention methods are used to avoid the occurrence of deadlocks. Some of these methods include designing traffic control rules, path reservation systems or multi-agent protocols to guarantee that a fleet of robots never enter a circular wait state.

If a deadlock does occur, a deadlock resolution strategy is employed. These strategies aim to resolve the circular wait condition conflict.

This article focuses on examining deadlock resolution strategies, not prevention strategies.

1.3 CURRENT DEADLOCK RESOLUTION STRATEGIES

One of the main deadlock resolution strategies used today involves replanning the robots' trajectories. In cases like [2], the robots are represented as nodes in a graph and deadlocks are represented as circles between the nodes. The goal of the deadlock resolution algorithm is to break those circles by planning an alternative trajectory.

Alternatively, heuristic methods can be used to resolve deadlocks. One heuristic example is to introduce random perturbations in the robot's movement, the reason being that deadlocks are often caused by symmetrical conditions, and small random movements are effective in breaking that symmetry [3], [4].

Another heuristic deadlock resolution strategy is the right-hand rule, where robots facing each other move to their right side to resolve the deadlock [5].

Although simple to implement, heuristic methods offer no guarantee that the deadlock will be resolved and sometimes pose safety risks or can lead to livelocks [6].

1.4 TELEOPERATION AS A DEADLOCK RESOLUTION STRATEGY

Teleoperation, or Remote Human Intervention, is typically used as a fallback, when a deadlock resolution strategy has failed. In such cases, a human operator connects remotely to one of the robots and controls it manually to resolve the deadlock. There are different methods which teleoperators can utilize to resolve a deadlock.

The most direct control method is to drive the robot manually. Human operators are able to take bigger risks than AMRs, e.g. driving closer to obstacles or navigating difficult terrain, which allows them to resolve deadlocks which are unmanageable for an autonomous system.

Alternatively, the operator can set a new intermediate goal for the robot. In these cases, the robot recalculates its path and escapes the deadlock without needing to be manually driven.

Lastly, when a malfunction causes a robot to block a shared resource, a teleoperator can resolve the deadlock by restarting a sensor, a software node or the whole robot. For example, when an AMR loses its localization, a teleoperator can send it its current pose or clear its global costmap of obstacles that are no longer there.

In order to determine how effective teleoperation is as a deadlock resolution strategy, we need to be able to compare it to at least one other strategy. To make this comparison, we need to have common performance metrics for both strategies. However, no set of common parameters was found that would allow us to comprehensively compare different deadlock resolution strategies. To fill this research gap, this article defines a unified set of common performance metrics for deadlock resolution strategies. This set is then used to evaluate teleoperation as a deadlock resolution strategy in a simulated experiment.

2 LITERATURE REVIEW

2.1 CURRENT PERFORMANCE METRICS

Studies that propose a deadlock resolution algorithm usually report whether the robots reached their goals and how long that took. Chandra et al. [7] evaluated a control barrier function method in a doorway, corridor and intersection scenario using success rate, collision rate, stop time, time to goal, change in velocity, path deviation and flow rate. Similar performance metrics are used in decentralized control studies [8], where success is defined by all robots arriving within a fixed time limit (e.g., two minutes), alongside reported values for makespan and mean arrival time. In multi-agent pathfinding, the corresponding parameters are the share of instances resolved within a maximum number of time steps and the mean episode length [9]. Chen et al. [10] follow the same pattern for their model predictive control based scheme: deadlocks are detected online and the resolution is judged by whether trajectories remain feasible and goals are reached. The performance metrics they use are success rate and computation time.

Another common performance metric is makespan, or mission time, which is the duration of the whole task, whereas stop time and episode length isolate the interval in which the robots are stuck. Distinguishing these parameters is important because a strategy can resolve a deadlock

quickly and still send the robots on long detours afterwards. Both parameters are needed to comprehensively describe a strategy, which is why the metric set defined in the next chapter separates mission duration from deadlock duration.

Energy consumption is becoming an increasingly important metric for deadlock resolution strategies. Małopol-ski et al. [11] compared two deadlock handling methods, a “Chain of Reservations” and a “Structural On-line Control Policy”, in a simulation model of a production environment built on measured automated guided vehicle electricity data. They evaluated total energy consumption in kWh, task completion time and vehicle utilization, and found that configurations that finish tasks faster consume more energy. Studies of larger warehouse fleets include system-level parameters, such as throughput and waiting time per transport order [12], [13]. In [12], the throughput under a deadlock prevention strategy fell once the fleet grew past roughly five to seven vehicles, because waiting time per order rose with congestion.

2.2 METRIC PRIORITY

Which metric has the highest priority when evaluating a strategy depends on the robots’ use case.

In warehouse fulfillment, a stalled robot blocks orders, which is why time-based parameters are most important in [12] and [13]. For battery-constrained fleets, energy is the binding constraint. For instance, in [11] low energy consumption is treated as an objective equal to fast completion time. This constraint is even more pronounced for outdoor delivery robots, as locomotion dominates the energy budget of ground robots, and surface type alone can more than double consumption [14]. In spaces shared with people, safety has the highest priority. Metrics related to safety include path deviation and collision rate [7].

No single metric is sufficient on its own, and the field has started to acknowledge this by reporting multi-criteria results [11]. This supports the approach taken in this article, which defines a set of complementary metrics rather than one score to evaluate a deadlock resolution strategy.

2.3 TELEOPERATION IN THE FIELD OF AMRS

Teleoperation is viewed in the field of AMRs as a supervision and fallback mechanism rather than as a deadlock resolution strategy in its own right, and is therefore evaluated with different parameters. Studies of operator performance report task completion time, distance travelled, average speed, control effort and perceived workload, as relevant performance metrics [15]. In the field of AMRs important parameters include how often humans intervene, disengagement rate and miles per intervention [16]. Recent work has shifted toward remote assistance, in which the operator issues high-level commands instead of steering directly [17], and toward analyses of when and why safety drivers intervene during remote driving [18].

Reviews of AMR planning and control in intralogistics list deadlock handling among the open control problems, yet none of them treat teleoperation as a resolution option [19], [20].

2.4 RESEARCH GAP

The processes of teleoperation and autonomous navigation share many common performance metrics. However, in the field of deadlock resolution, these metrics are not being compared.

In the field of teleoperation, intervention counts indicate how frequently human assistance was required, while operator metrics describe the cognitive or physical demand imposed on the human. However, neither approach captures the critical parameters established in deadlock-resolution literature: whether the robots reached their goals, the duration of blockages, the distance traveled, or the energy consumed. The reverse also holds. Existing deadlock-resolution studies either exclude teleoperated scenarios or fail to account for the specificities of remote operation; consequently, the metrics reported in [7]–[13] have not been evaluated in the context of teleoperated recovery. Teleoperation therefore cannot be compared with algorithmic deadlock resolution strategies such as trajectory replanning [2] or heuristic perturbation [3], [4] on any common scale, even though it is routinely used in practice when those strategies fail.

This article addresses the research gap by defining performance metrics that apply to autonomous strategies and to teleoperation alike, and by measuring them in a simulation experiment in which a teleoperator resolves a deadlock between two autonomous warehouse robots.

3 METHODOLOGY

3.1 DEFINING THE PERFORMANCE METRICS

Based on the performed literature review, we have defined the following performance metrics for deadlock resolution strategies, including teleoperation. These metrics can be used to evaluate any given deadlock resolution strategy from different aspects and compare it to another.

Mission result - Indicates whether all the robots overcame the deadlock to reach their goal without falling into another deadlock, leading to the so called livelock. The value of this parameter is “Success” if all robots reach their goals, otherwise it is “Fail”. It is important to avoid failures due to other reasons such as a collision or out-of-bounds violation. The mission result should depend solely on the deadlock resolution strategy for the comparison between strategies to be fair.

Mission duration - shows how much time it took for a robot to reach its goal. It is useful when trying to find the fastest overall strategy.

Deadlock duration - shows how long the robots were stuck motionless or otherwise blocked, in a deadlock. It is useful for finding the strategy that resolves the deadlock the quickest, regardless of the time it will take the robots to reach their goals afterwards.

Number of deadlocks - can be used to determine if the given strategy leads to more or less deadlocks compared to another strategy.

Travel distance - is the distance travelled by a robot for an entire mission. This parameter can be used to find the strategy with the best path planning. It can also be used to evaluate the ecological impact of a given strategy, depending on the fuel type of the robots, as well as estimate the mechanical degradation of the robots.

Power consumption - is the electrical energy consumed by a robot during one entire mission. It is measured in Watt-hours (Wh). The metric is essential for evaluating the sustainability of a given strategy and for identifying the most suitable approach for applications with highly constrained battery capacities. Its calculation is given in equation (1).

$$E = \int P(t)dt = \int V(t)I(t)dt \quad (1)$$

The discrete approximation of equation (1) is:

$$E = \sum_{i=1}^{N_M} V_i I_i \Delta t \quad (2)$$

where:

- E is the electrical energy consumed by the robot;
- N_M is the number of measurements;
- Δt is the measurement interval, i.e., the time between consecutive measurements.

Robots can record the voltage and current readings of a coulomb meter, connected to their battery, to calculate their energy consumption for one mission by solving equation (2).

These performance metrics can be used to evaluate a deadlock resolution strategy from different aspects. Depending on the scenario, a high success rate is not the only important characteristic for a deadlock resolution strategy. For example, in intralogistics scenarios, a lower mission duration can be more important than low power consumption, because the robots can quickly be replaced by those

waiting in reserve. Outdoor delivery robots on the other hand prioritize lower power consumption and travel distance to mission duration. Whatever the case may be, the defined performance metrics can be used to evaluate different deadlock resolution strategies and choose the best one for the given use case. Furthermore, they can be used to calculate additional performance metrics such as: the success rate of a given strategy, the average speed of the robots, the state of charge of the robots' batteries at the end of a mission, etc.

3.2 DEFINING THE CONSTRAINT PARAMETERS

When using the performance metrics to compare multiple deadlock resolution strategies, it is important to ensure that the strategies were evaluated under the same conditions.

In order to ensure a fair comparison between different strategies, the following mission constraint parameters were defined.

Maximum speed - specifies the highest speed the robots can drive with. It is useful for describing a scenario precisely, rather than using vague terms, such as "high speed". It can also have a significant effect on key performance metrics, such as mission duration and total power consumption.

Maximum mission duration - limits the amount of time that a mission can last, in case a deadlock resolution strategy leads to livelock, or simply takes too long to be acceptable for the given use case. This parameter also ensures that a mission cannot last forever, in case a robot's battery is depleted before reaching its goal, for example. If the robots do not reach their goals in the specified time limit, the mission result will be "Fail".

Number of robots - specifies how many robots have participated in the experiment. Increasing this parameter can increase the congestion level of the environment.

Number of teleoperators - specifies how many people have taken control of a robot during the experiment. If the parameter's value is 0, the compared strategies utilize only autonomous robots. A value greater than zero means that this number of robots have been teleoperated during the experiment.

Total area - the area of the environment where the experiment was performed.

Robot area - specifies the area of a robot's footprint, which is the 2D outline of its shape when projected onto the ground.

Obstacle area - is the sum of all the areas occupied by obstacles, excluding the robots.

Deadlock area - the sum of all the areas where no two robots can pass each other, like narrow passages for example. This metric is essential when comparing strategies across different environments. A larger total area does not necessarily imply greater maneuverability for deadlock resolution. For instance, increasing the length of a narrow passage expands the deadlocking area without providing additional space for robots to resolve a conflict.

Area type - specifies whether the area is indoor or outdoor.

As with the performance metrics, the constraint parameters can also be used to calculate additional parameters, such as the drivable area, maneuverable area, congestion level of the environment, etc.

$$A_D = A_T - A_O \quad (3)$$

where:

- A_D is the drivable area;
- A_T is the total area;
- A_O is the obstacle area;

$$A_M = A_D - A_{DL} - (A_R \times N_R) \quad (4)$$

where:

- A_M is the maneuverable area;
- A_{DL} is the deadlock area;
- A_R is the robot area;
- N_R is the number of robots;

$$C = \frac{(A_R \times N_R)}{A_D} \times 100 [\%] \quad (5)$$

where:

- C is the congestion level of the environment;

3.3 SIMULATION EXPERIMENT

To evaluate teleoperation as a deadlock resolution strategy and assess the suitability of the defined parameters, an experiment was performed in a simulated environment by comparing three scenarios:

- One autonomous robot against another autonomous robot (1A-vs-1A).
- One teleoperated robot against an autonomous robot (1T-vs-1A). The teleoperated robot in this scenario was "bot_1" and the autonomous robot was "bot_2".
- One teleoperated robot against another teleoperated robot (1T-vs-1T).

In each scenario, the robots were spawned in the exact same location to ensure that they were an equal distance from their respective goals. The goal of robot 1 (bot_1) is position 'A' and the goal of robot 2 (bot_2) is position 'B', see Figure 1.



Figure 1. Experiment overview for all three scenarios

The symmetrical map layout and narrow aisles were intentionally designed to increase the likelihood of a deadlock occurring. Each scenario was performed five times to acquire more representative data.

The simulated environment was created in Gazebo Harmonic and the autonomous warehouse robots were programmed with the Nav2 stack for ROS2 Jazzy [21].

4 RESULTS

While performing the experiment, we recorded the movement of the robots in the simulated environment, as well as their sensor readings, to ensure that the mission result depends on the deadlock resolution strategy and not some type of malfunction. Screenshots of the recordings are shown in Figure 2, Figure 3, Figure 4 and Figure 5.

The performance metrics measured during each scenario are shown in Table 1, Table 2 and Table 3. The constraint parameters of the experiment are listed in Table 4. The measurements were performed over the video recording of each mission due to time constraints. The Rviz timer, seen on the bottom left of Figure 2 - Figure 5, was used to measure the mission duration and deadlock duration, whereas a ruler was used to measure the travel distance and area sizes in Table 4.

The autonomous robots used in this experiment calculate their path using the “Navfn Planner” plugin [22], which implements a wavefront Dijkstra algorithm. When the two robots get close to each other, as shown in Figure 2, the lidar sensors allow the robots to detect each other. The newly detected object gets added to the local and global costmaps of the respective robot and a new route is calculated to avoid the obstacle.

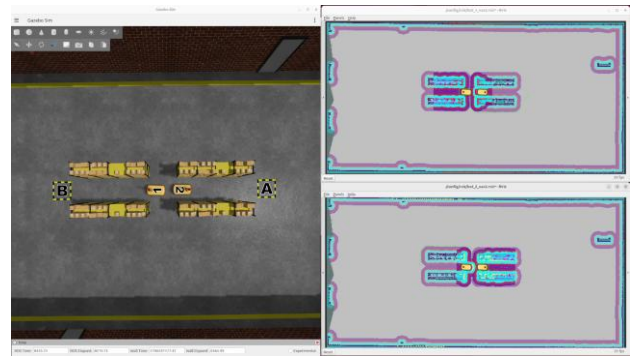


Figure 2. Deadlock between bot_1 and bot_2. (left) Simulated environment, (top right) sensor data for bot_1, (bottom right) sensor data for bot_2. Screenshot from scenario 1A-vs-1A, mission 1

In this way, the robots were able to resolve the deadlock without the ability to communicate, as shown in Figure 3. During the 1T-vs-1T missions, however, the teleoperators were able to communicate and make a strategy on how to pass each other.

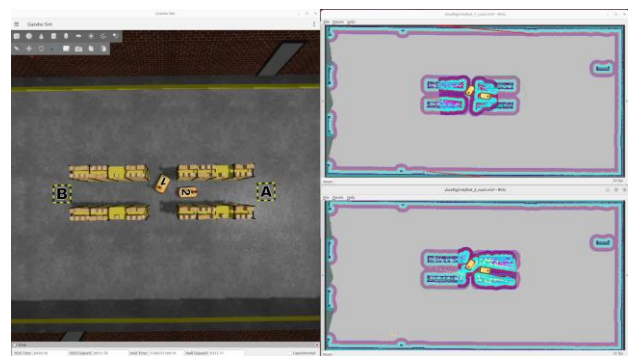


Figure 3. Successful deadlock resolution. Screenshot from scenario 1A-vs-1A, mission 1

When the robots are able to pass each other by following the newly calculated route, the deadlock is resolved successfully, as shown in Figure 3 and they reach their goal positions, as shown in Figure 4.



Figure 4. Successful mission result. Screenshot from scenario 1A-vs-1A, mission 1

Sometimes, however, the robots are unable to follow the newly calculated path due to the limited maneuverable

area. In such cases the robots might lose their localization or get stuck between obstacles, unable to proceed without manual intervention, as shown in Figure 5. In those cases, the robots will fail their mission due to exceeding the maximum mission duration specified in the constraint parameters.

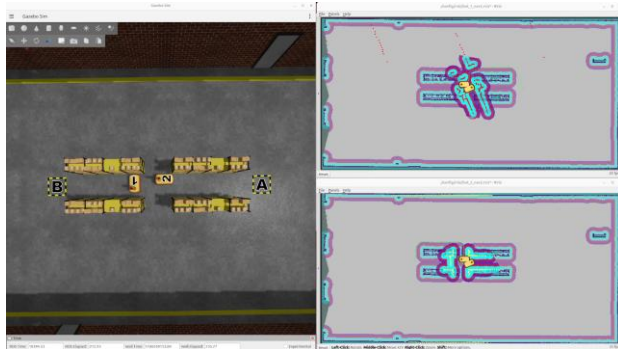


Figure 5. Failed deadlock resolution. Screenshot from scenario 1A-vs-1A mission 5

Table 1. Performance metrics for scenario 1A-vs-1A.

#	MR	MD_1 [s]	MD_2 [s]	DD [s]	TD_1 [m]	TD_2 [m]
1	S	34.180	40.440	8.630	12.20	12.20
2	S	41.060	52.450	8.240	14.25	14.84
3	S	29.420	43.910	0.000	10.74	13.66
4	F	-	-	∞	-	-
5	S	39.010	48.890	7.560	13.18	14.64
Avg:	80%	35.918	46.423	6.107	12.59	13.84

Note: MR = Mission Result, S = Success, F = Fail, MD_1 = Mission Duration for bot_1, MD_2 = Mission Duration for bot_2, DD = Deadlock Duration, TD_1 = Travel Distance for bot_1, TD_2 = Travel Distance for bot_2.

Table 2. Performance metrics for scenario 1T-vs-1A.

#	MR	MD_1* [s]	MD_2 [s]	DD [s]	TD_1* [m]	TD_2 [m]
1	S	20.690	43.320	0.000	7.91	13.66
2	S	29.370	37.970	0.000	18.45	10.93
3	S	20.800	37.730	5.670	15.81	10.25
4	S	16.360	30.100	2.610	11.71	10.74
5	S	22.160	34.270	0.000	16.40	11.03
Avg:	100%	21.876	36.678	1.656	14.055	11.322

Note: (*) In this scenario, bot_1 was teleoperated. For a list of abbreviations see Table 1.

Table 3. Performance metrics for scenario 1T-vs-1T.

#	MR	MD_1 [s]	MD_2 [s]	DD [s]	TD_1 [m]	TD_2 [m]
1	S	14.170	19.430	0.000	8.78	10.54
2	S	20.070	20.010	0.000	8.30	7.81
3	S	35.330	10.880	0.000	23.23	8.39
4	S	10.180	22.950	0.000	8.00	15.71
5	S	23.290	16.430	0.000	10.64	11.32
Avg:	100%	20.608	17.940	0.000	11.791	10.756

Note: For a list of abbreviations see Table 1.

During the experiment there was never more than one deadlock occurrence per mission. To reduce the size of the tables, this parameter was omitted. Therefore, it should be considered that wherever the deadlock duration equals 0 s, the number of deadlocks was also zero and wherever the deadlock duration was longer than 0 s, then only one deadlock had occurred.

The power consumption was not measured during this experiment because the simulated robot models lacked the necessary sensors. Nevertheless, the value of this parameter can be estimated using the average speed and mission duration for each robot, provided that the power characteristics of the robot are known beforehand.

Table 4. The constraint parameters for all three scenarios

Max Speed	1 [m/s]
Max Mission Duration	3 [min]
Number of Robots	2
Number of Teleoperators *	0 / 1 / 2
Robot Area	0,79 [m ²]
Obstacle Area	8,47 [m ²]
Deadlock Area	8,66 [m ²]
Total Area	380.15 [m ²]
Area type	indoor

Note: (*) value depends on the scenarios 1A-vs-1A, 1T-vs-1A and 1T-vs-1T

4.1 ANALYSIS

Despite the experiment being conducted with only two robots, valuable insights can be gained about these deadlock resolution strategies based on the measured performance metrics.

Firstly, the data shows that humans worked more efficiently with other humans than they did with the autonomous mobile robot.

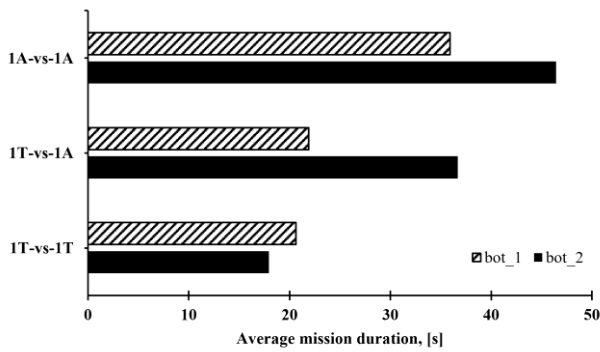


Figure 6. Average mission duration for each robot in each scenario. In scenario 1T-vs-1A, bot_1 was teleoperated

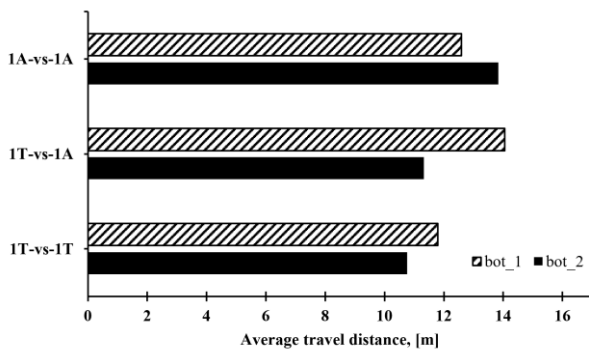


Figure 7. Average travel distance for each robot in each scenario. In scenario 1T-vs-1A, bot_1 was teleoperated

In scenario 1T-vs-1A, one would expect that the teleoperated bot_1 would have a shorter travel distance than the autonomous bot_1 in 1A-vs-1A. However, as shown in Figure 7, the travel distance for bot_1 increases. This is because the teleoperator did not know what the autonomous bot_2 was going to do, so the teleoperator often chose longer routes that avoided conflicts between them. However, when bot_2 was replaced by a teleoperator in 1T-vs-1T, both the mission duration and travel distance parameters were reduced, because the teleoperators could communicate and strategize together. As a result, it was concluded that our teleoperators worked more efficiently with each other than they did with the autonomous robot.

Secondly, the performance of the AMR bot_2 was improved when a teleoperator took control of bot_1. As shown in Figure 6 and Figure 7, when bot_1 was teleoperated in 1T-vs-1A, both the mission duration and travel distance of bot_2 were reduced as compared to their values in 1A-vs-1A, despite bot_2 having the same configuration in both scenarios. This is of course caused by the teleoperator's ability to avoid deadlocks and resolve them faster when they do occur, as shown in Figure 8.

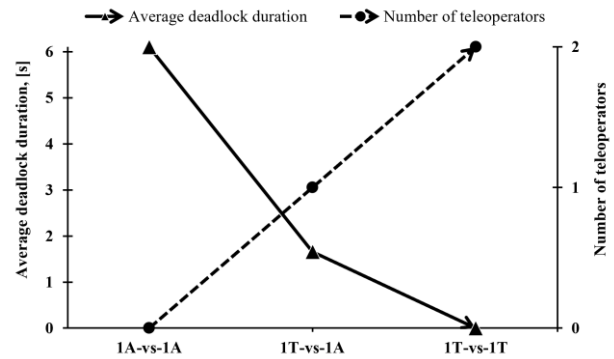


Figure 8. Correlation between the average deadlock duration for each scenario and the number of teleoperators

In fact, increasing the number of teleoperators significantly reduced the average deadlock duration for each scenario to the point where teleoperating both robots eliminated the occurrence of deadlocks entirely.

Lastly, increasing the number of teleoperators also increases the average speed of the robots, which is strongly related to their power consumption.

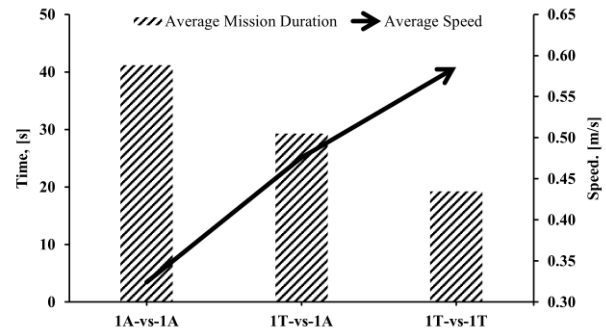


Figure 9. Correlation between the average mission duration for both robots and the average speed of both robots for each scenario.

The average speed of both robots for a given scenario, shown in Figure 9, was calculated using equation (6).

$$v_{AVG} = \frac{v_{AVG_1} + v_{AVG_2}}{2} \quad (6)$$

$$v_{AVG_1} = \frac{\sum_{i=1}^N TD_i}{\sum_{i=1}^N MD_i} \quad (7)$$

where:

- v_{AVG} is the average speed of both robots for a given scenario;
- v_{AVG_1} and v_{AVG_2} are the average speeds of bot_1 and bot_2 respectively;
- N is the number of missions in the scenario;
- TD_i and MD_i are travel distance and mission duration, whose values can be found in the table of performance metrics for the given scenario.

Although in all three scenarios, the maximum speed of the robots was set to 1 m/s, the autonomous robots never actually reached that speed due to the computational time required to perform autonomous navigation. The AMRs drove slower to have enough time to calculate their next step. The maximum speed the autonomous robots actually reached was around 0.5 m/s on each mission. The teleoperators, on the other hand, were able to drive the robots at the maximum allowed speed of 1 m/s, improving the performance metrics Mission Duration and Travel Distance at the expense of higher power consumption.

It is expected that by increasing the number of robots, the differences between the scenarios will become even more pronounced. Nevertheless, in those cases the same performance metrics can still be used to evaluate the given strategies.

Another benefit of the proposed performance metrics is that they can be measured automatically during each experiment and exported afterwards. They simplify the process of evaluating deadlock resolution strategies, thus allowing researchers to focus on conducting more experiments to gather more data and make more informed decisions. Using the same parameters to evaluate different strategies makes it much easier to compare them.

For the current experiment, the performance metrics show that the scenario with the highest success rate, lowest mission durations, lowest travel distances and lowest deadlock durations is the one where both robots are teleoperated, 1T-vs-1T.

Based on this data, it can be concluded that it is better to assign multiple teleoperators to work together on a single scenario than it is to assign one teleoperator per scenario. However, assigning more people to a task increases costs, which may be further increased by larger energy costs, depending on the average driving speed and the robots' power consumption.

One possible way to reduce costs while increasing productivity and performance is to have a central system that matches available remote teleoperators to a task and connects them to the necessary robots. An operational control center (OCC), like the one proposed in [23], could reduce costs by eliminating the need to have teleoperators be on-site even when there are no issues with the AMRs. The performance of the teleoperators will depend on many factors, one of which is their ability to communicate with each other. The OCC must allow teleoperators to easily communicate and offer them the tools necessary to create a successful strategy, such as a map of the environment and low-latency live sensor data.

5 CONCLUSION

In order to effectively evaluate teleoperation as a deadlock resolution strategy, one has to consider the common performance metrics between it and other strategies and analyze the results from different aspects, depending on the use case. During our simulation experiment, the performance metrics defined in this article proved to be effective in showcasing the benefits and drawbacks of each strategy. Additional metrics, such as average speed, could be calculated based on the measured parameters, which enabled us to make a more thorough analysis. The performance metrics also allowed us to make interesting observations, such as the correlation between the deadlock resolution time and the number of teleoperators, as well as the cost that comes with the increased performance of the 1T-vs-1T scenario.

Ultimately, the scenario where both robots were teleoperated (1T-vs-1T) proved to be the best option for increasing the success rate, eliminating the deadlock duration, reducing the mission duration and travel distance but it comes at the cost of having two teleoperators and higher energy consumption due to the higher average speed of the teleoperated robots.

More importantly, the experiment showed that teleoperation can be a highly effective deadlock resolution strategy, especially when the number of teleoperators is increased. On the basis of these findings, it is suggested that future research should focus on facilitating the integration of teleoperation into the workflow of AMRs, e.g., by developing an operational control center. Furthermore, it would be interesting to see how the performance metrics would change when more robots are added to the simulation and given the ability to communicate and strategize together.

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