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Final Report - Towards Cognitively Intelligent Vehicles

Topic: Global Path Planning and Obstacle Avoidance for Autonomous Unmanned Surface Vehicles using Multi - Objective Improved Grey Wolf Optimisation (MOIGWO) - Vehicle Routing Problem using Waypoints

August 2nd, 2021

Targeting Paper Conference:

1. 2nd IFSA Winter Conference on Automation, Robotics & Communications for Industry 4.0 (ARCI' 2022) : 2-4 February 2022 in Andorra la Vella, Andorra.
2. IEEE Intelligent Transportation Systems Society Newsletter

Aim of the Project:

Implementation of novel Multi Objective Improved Grey Wolf Optimisation (MOIGWO) algorithm for USV Global Path Planning Problem with water current effect in the context of Task2 of Maritime International RobotX Challenge 2022.

Abstract:

The interest in Autonomous Unmanned Surface Vehicles has increased substantially over the years due to its extensive use in defence and medical applications. Its ability to monitor and perform dangerous tasks in marine environments reducing the risk of humans has led to many researchers delving into Path Planning of USVs to increase its efficiency and to meet its real time goals. The purpose of this research was to explore the Global Path Planning of USV to travel from its initial to final point via specific waypoints, avoiding various obstacles along the way satisfying multiple objectives such as path smoothness, shortest path length and path safety taking into consideration the major environmental factor, water current and its effect on path planning. The main constraints considered were boundary, angle and velocity and four major experiments were conducted to identify the right number of parameters before the simulation analysis was done. Optimal paths were generated for 2 and 3 objective problems, its versatility to adapt to different maps was tested and was found to generate suitable paths for all situations with a 80% accuracy across various simulations. Compared to the original MOGWO and popular algorithm MOEA/D , MOIGWO was found to provide superior paths for fixed water current in lesser runtime and was also tested on time varying currents. MOIGWO was further evaluated against the ZDT3, multi-objective benchmark function using the standard metrics of IGD, Spacing and Maximum Spread. Taking one of the tasks of Maritime RobotX 2022 Challenge as the context to solve, a novel multi objective parameterization method using nature inspired Grey Wolf metaheuristic optimization method has been proposed in the paper and the optimal paths have been selected using Pareto Optimal Solutions.

The following has been implemented in this project:

1. Implementation of a technologically better solution of the existing Grey Wolf Optimization Algorithm for Global Path Planning Problem of Unmanned Surface Vehicles taking into account only water current effect.
2. Grey Wolf Optimization, providing superior solutions for mobile robotics path planning problems was identified and 3 improvements have been made to this algorithm
    a. Inspired by the Particle Swarm Algorithm, the learning of the position of wolves for the next iteration takes both Social Harmony (learning from the best three solutions alpha,beta and delta wolves) as well as Individual Memory (with respect to previous best position) to reach the optimal solution.
    b. Introduced non linearity in ‘f’, which was previously linearly decreased from 2 to 0. The modification that I have brought about is to reduce it exponentially from 2 to 0. This enables the discriminiation weight coefficient A to increase the exploration in the initial iterations, focus on exploitation near the end and improve its convergence rate.
    c. Introduction of Chaos to the parameter C (random mutation coefficient) in Original GWO thereby improving the tradeoff between exploration and exploitation. This has been done by using a 1-D sinusoidal map with values ranging from 0 to 1.
3. An appropriate Map/ Environment has been created for visualisation of the Path generated by the Improved GWO algorithm. The dimensions of the course boundary, obstacles, gates and USV have been taken from Task2 of the Maritime International RobotX Challenge 2022.
    a. Static obstacles and gates with known coordinates are provided as inputs. Randomness in map has been generated by random angle generation between left and right gates and in the selection of number of waypoints and obstacles in the path from starting to end point.
4. Global Path Planning is a multi-objective problem and 3 main objectives have been minimised:
    a. Shortest Path Length
    b. Path Smoothness
    c. Path Safety

5. Three main constraints have been taken into account:
   a. Boundary Constraint: Points generated should be within the boundaries
   b. Safe Area Constraint: Points generated should not lie within the obstacles or gates minimum radius
   c. Velocity Constraint: Points/ USV should move towards the destination
6. 2 scenarios, Fixed Current Direction and Time Varying Current Direction have been simulated to test the real case viability of the path generated. A East - West generating wave function has been implemented and corresponding velocities have been added to initial USV velocity in the X and Y direction.
7. The leaders or wolves (alpha,beta and delta) with best positions are chosen using the Roulette Wheel Probability and the positions of other wolves have been updated. An external Archive is maintained where positions of wolves (USV's possible positions in its path from start to end point) are stored. This archive is updated by selecting non dominating solutions satisfying the Pareto Front.
8. At the end of Maximum Time iteration, the costs of each solution is normalised and using a Preference Set P, the best solution with the minimal total cost is returned as the Path taken by the USV.
9. Multi Objective Optimisation Algorithms MOEA/D (Multi Objective Evolutionary Algorithm/ Decomposition) has also been executed for this problem to test the proposed Multi Objective Improved Grey Wolf Optimization and the costs obtained on satisfying the Objectives.
10. The following experiments have been carried out:
    a. Varying the Number of Grey Wolves used, Maximum number of Time Iterations, External Archive Size and Number of decision variables between start and end point to obtain minimum cost values in minimum run time
    b. Using a standard Map and testing the Optimal Path generated for 2 and 3 objective problems for fixed direction of water current
    c. Comparison on standard Map of path and costs of MOIGWO with MOGWO and MOEA/D for fixed direction of water current
    d. Generating paths for 5 random maps with optimal route for each.
    e. Implementation of MOIGWO for Time varying Currents
    f. Validated against ZDT3, multi-objective benchmark function using 3 standard metrics (IGD, Spacing and Maximum Spread)
11. All the codes generated have been shared at the end of this report.

Introduction:

Exploration of oceans and water bodies which cover approximately two thirds of the world's surface [1] has been a fascination and interest for humans for ages. There has been sudden interest in increasing the efforts put in research and development to find safe yet efficient ways to tackle the dangers of the seas and oceans without putting humans at risk. Climate change, environmental abnormalities, personnel requirements, and national security issues have all led to a strong demand from commercial, scientific, and military communities for the development of unmanned surface vehicles (USVs). [2]

It is possible to use USVs for maritime operations to carry out dangerous tasks beyond the abilities of human capability due to USVs features of coordinated cooperation, strong autonomy and powerful field operational advantages for search missions and reconnaissance operations. It has some autonomous functions such as accurate strikes, cyclical operations, self destruction and rapid evacuation due to which the importance given to path planning and path control has increased substantially over the last few years.[3]

One of the biggest challenges that unmanned surface vehicles face when travelling from one location to another is safety navigation, avoiding the obstacles along its path and planning of conflict free paths is of tantamount importance. Having established the importance of path planning for USVs there have been multiple efforts in path research in trying to find an accurate solution using classical algorithms. However its effectiveness reduces as complexity of the problem increases.

The USV path planning is a time varying nonlinear programming problem and is a sub problem of the NP - Hard problem set. Optimization methods and algorithms can be classified in many types, but the simplest way is to look at the nature of the algorithm and group them into stochastic and deterministic where techniques that are deterministic rely on the characteristics of the problem, while stochastic techniques does not rely on the functions of the mathematical properties and hence are more suitable for discovering the most optimal global solutions for all kinds of objective function. However, the drawback of the first method are its local optima, dependence on gradient and inefficient in extensive space search and cannot solve discrete functions. Stochastic techniques are more user friendly to be considered. As the complexity of several actual optimization problems increases, it is inevitable to use stochastic techniques. [4]

The paper is organized as follows:

First the Maritime International RobotX Challenge has been discussed and the chosen task is mentioned in detail.

Second, Literature Review of existing methods in Global Path Planning is discussed and Problem Formulation is explained where the path is planned via a set of waypoints from the starting point to the final destination.

Third, the problem is formulated, constraints are mentioned and three objectives are introduced which the USV must satisfy while safely navigating across static obstacles in its course taking into account the effect of both fixed and time varying water currents.

Fourth, the proposed algorithm is elaborated and the improvements brought about to the original GWO are elucidated, the concept of Optimal Pareto Solutions is mentioned and the method in selecting the final solution is defined.

Fifth, The algorithm of MOIGWO is explained for the Global path planning problem for both scenarios of current effect.

Sixth, Selection of parameters by conducting a set of experiments

Seventh, Simulation analysis has been conducted to show the implementation of the proposed algorithm and compared with the popular algorithm MOEAD.

Eighth, Validation of the proposed algorithm was performed using three standard metrics IGD, Spacing and Maximum Spread for the ZDT3 Benchmark Function

Ninth the paper concludes with the results

Finally, the future scope of this project to test its practical viability in real scenarios.

1. USV Design and Environment

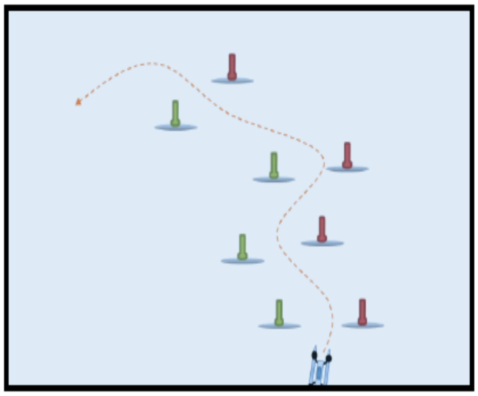
1.1 Environment and Context:

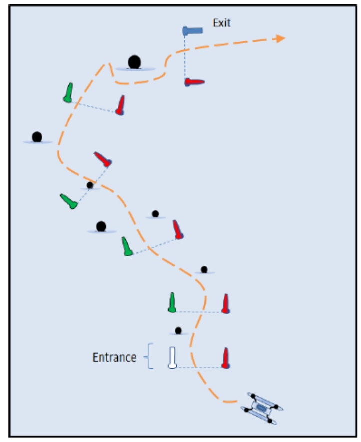
The 2022 Maritime Robotx Challenge is an international maritime robotics competition where the world leading institutions are invited to participate. They are provided with a standardised platform, the Wave Adaptive Modular Vehicles(WAM - V) and an Unmanned Aerial Vehicle(UAV).

The competition is a bi annual event where teams develop a fully autonomous system able to complete a set of complex tasks which have been conceptualised to mimic real world challenges and provide students with an insight on how to tackle various maritime challenges.

Focussing on navigation, path planning and obstacle avoidance as the topic of this paper, ‘Follow the Path’ task has been used as a context for the implementation of the metaheuristic algorithm. This task takes its modifications from the 2019 Virtual RobotX Challenge “Traverse Navigation Channel” and the task description is used to create the environment and used to experiment the functioning of the algorithm proposed.

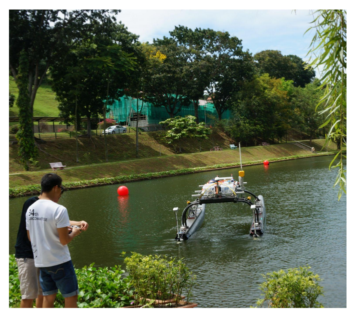
As compared to previous year challenges, the tasks have been slightly modified and the use of an **Unmanned Aerial Vehicle** has been introduced.





An UAV is deployed by the AMS and the vision system present in the UAV uses image processing to identify the gate buoys cross referenced with the dimensions and colour of the gate buoys and the coordinates are returned to the Path Planner with which the Global route is planned.

A local path planner with lidar sensors is then used to make sure the WAM - V is able to follow the path planned by the Global planner taking into account the variations of the environment that includes wind, waves and current effects.



The AMS must transit through the path marked by the pairs of red/green coloured buoys without striking any obstacle. The boat should traverse a linear course bounded by two sets of gate buoys with different colors (red on the port side and green on the starboard side) at the start and end points. The boat should enter the course through a designated entry gate, navigate the course area filled with different sizes of obstacle buoys without collision (or contact), and complete the course by passing through a designated exit gate. [23]

1.2 Assumptions and Formulation

The implementation of the proposed algorithm is from the following rationale as mentioned by the authors in [24].

1. Obstacles and gates in question are assumed to be static.
2. The boundaries of the environment are known a priori (80m x 60m).
3. Dimensions of the detected obstacles can be easily contained within the boundary of our analysis.

Task Element	Description	Model No.	Ht. Above Waterline	Base Diam.
Field Boundary Marker	470mm Dia. Round Buoy (Orange)	N/A		
Start Gate Port Marker	650mm Dia. Marker Buoy (Red)	N/A	850mm	650mm
Start Gate Starboard Marker	650mm Dia. Marker Buoy (Green)	N/A	850mm	650mm
Obstacle	470mm Dia. Round Buoy (Black)	N/A		

The entrance gate is a white-red pair, the exit gate is a blue-red pair and the other gates are green-red pairs. Obstacles may be included within and around the navigation channel.

While the layout of a particular navigation channel will vary, all competition navigation channel runs will satisfy the following constraints:

- The width of a gate, measured as the distance between the two buoys making up the gate, will be between 5-15 m.
- The distance between gates, measured as the distance between the centroid of the two gate markers, will be greater than the maximum of the widths of the two closest gates.
- The number of gates in an individual run can be between 2 and 10.

[57] The main physical dimensions of **WAM-V** used in this study is shown in Table -1:

Parameters	Measurements
Length of USV	4.85m
Hull Length	3.91 m
Hull Diameter	4.26 m
Overall Vehicle Height	1.27 m
Overall Vehicle Width	2.44 m
Payload (Maximum)	136 kg
Full Load Displacement	255 kg
Draft	0.165 m
Primary Sensors	GPS, Camera, LRF, INS, Hydrophone - Pinger

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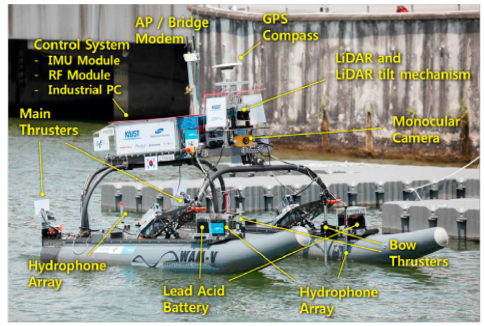
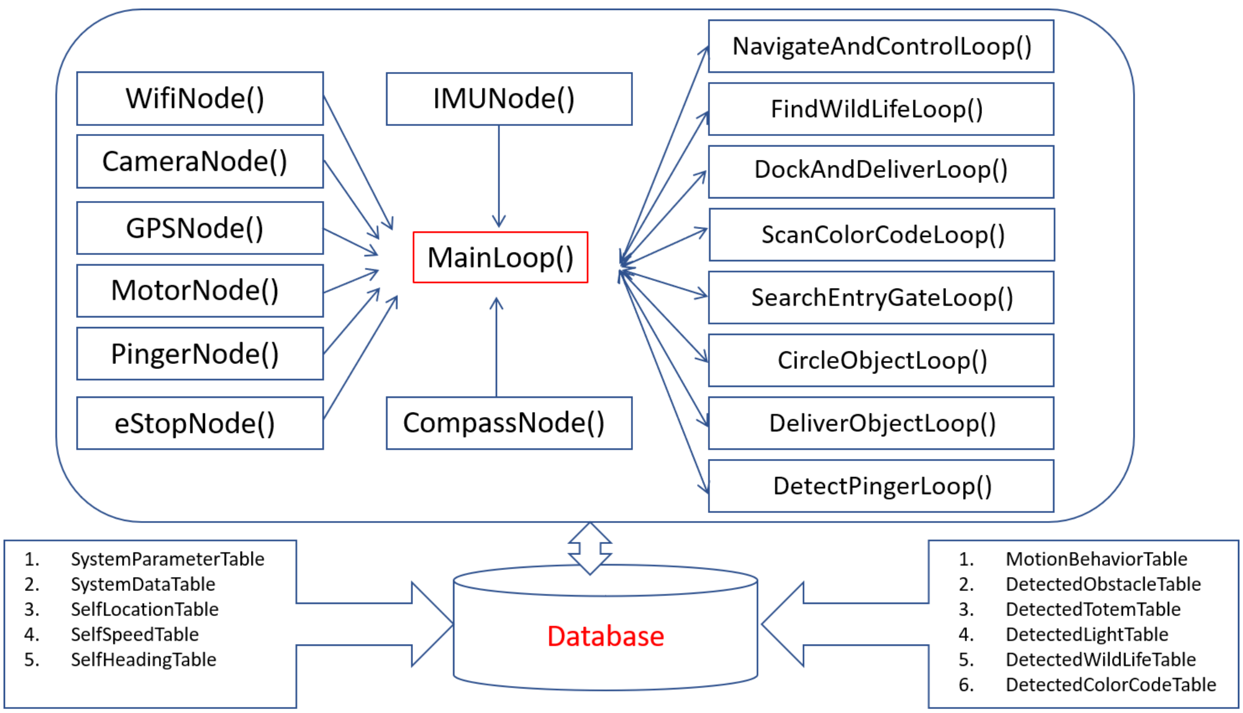


The following functions and nodes are present where the Wifi Node helps connect the WAM-V to the server on land. The camera and GPS nodes help to identify the totems, entry and exit gates and return the coordinates to the global path planner for path Planning. The totems are cross checked with the DetectedTotem Table to conclude the colour and type of gate. Obstacles identified by the camera and their coordinates are given as inputs from the DetectedObstacle Table for the navigate and control loop. The SelfSpeed and SelfLocation Table values are filled iteratively to bring the WAM-V back into the course and navigate within the boundaries of the course.



Global path planning is considered taking into consideration the dynamic environment where the major effect on the USV is only of water currents .

The problem has been simplified by taking the inputs of coordinates of the obstacles and gates after the UAV employed finishes charting the course. Taking the wave current, its velocity and direction as inputs at every waypoint, the path is planned iteratively from the initial starting point to the final destination for a finite time interval.

At every iteration, the velocity of the USV is calculated with respect to the direction in which the USV is facing towards the final destination and this is taken into account when the path planning process is executed by the Global Path Planner at every waypoint.

2. Literature Survey:

Heuristic algorithms can obtain solutions when accurate solutions lose effectiveness. Some of the effectual stochastic methods that imitate the behaviors of certain animals or insects (birds, ants, bees, flies) and are called Nature-Inspired Heuristic Algorithms have been developed since the 1980s.[6,7,8,9,10,11]

[12] The authors discuss the application of PSO (particle swarm optimization) and its modifications by various authors for path planning and have proposed Chaotic PSO to improve the path planning process of USVS taking into account multiple objectives providing two level collision avoidance.

[13] The authors analysed collision avoidance and synchronization motion tracking control of multiple under-actuated ships, [14] studied platoon formation control with prescribed performance guarantees for USVs. [15] proposed neural-network-based adaptive output-feedback formation tracking control of USVs under collision avoidance and connectivity maintenance constraints. [16] researched leader-follower formation control of USVs with prescribed performance and collision avoidance.

Many algorithms have been proposed such as Q-learning for smart ships path planning [17], A* approach towards optimal path planning for an unmanned surface vehicle containing dynamic obstacles[18], multi-layered fast marching method for unmanned surface vehicle path planning in a time-variant maritime environment [19]. Dijkstra search and energy consumption function are combined to solve path planning [20]. The GA algorithm solved path planning for autonomous underwater vehicles in a variable ocean [21] An improved GA for optimal search path planning for unmanned surface vehicles simultaneously optimizing speed and direction [22].

[3] There has been much attention for shortest path planning in robotics striving to generate paths that are conflict free, with the obstacles represented by certain shapes in a simplified environment. [25] stated that the shortest path can be found with modified incremental heuristic algorithms. [26] came up with a multiple criterion shortest path criterions global path planning for unmanned combat vehicles however the planning environment was oversimplified and little attention has been paid to environmental effects.

Much of the research work involves using high order polynomial functions to create a smooth path however may not be applicable to engineering problems [28,29] The path of the USV through the water surface is represented by line segments connected by a sequence of waypoints.

To improve the practicability of the planned path, many constraints including the effects brought by currents, the obstacles, and the motion boundaries, should be incorporated into the path planning model. Refs. [28,29,32] treated the obstacles as circles or spheres in two-dimensional or three dimensional space, respectively, and safety was embedded as a constraint of the path planning problem

Having done the literature review, this paper focuses on taking the three main objectives identified as path smoothness, shortest path distance and path safety while solving path planning problems.

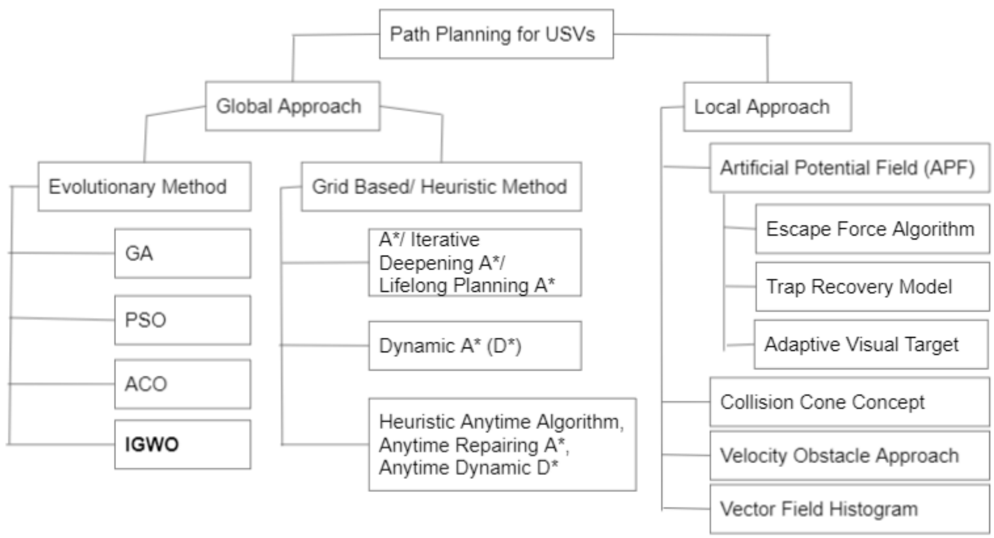
[33] The author provides a solution to implement the path planning techniques where mapping the environment becomes the initial step. Environment mapping can be qualitative or quantitative and converts world space into **configuration space or Cspace.** C Space for marine vehicles are dynamic in nature and are highly variable, spatially as well as temporally. Effect of current, wind and tides have to be incorporated into mapping so that a robust virtual real time environment can be generated.

Popular mapping techniques are meadow maps, Voronoi diagrams, regular occupancy grid and quadtree mapping which are grid based or metric techniques on which heuristic and evolutionary optimisation methods can be applied effectively. Regular occupancy grids are generated through superimposition of 2D Cartesian grid on Cspace. However, higher computational requirements are a major drawback of such techniques.

The path planning can be divided into 2 folds: **(i) Local Path Planning (ii) Global Path Planning.** In local path planning, the USV has limited knowledge (either partially known or unknown) about the navigational environment. In global path planning, the USV has complete knowledge about the navigational environment and thereby the USV can reach the final destination using a predefined path.

Offline or global approach is used when complete information about the marine environment is known while the online or local approach is used when the marine environment keeps changing during navigation of marine vehicles. Global approaches consist of evolutionary and grid based methods. Evolutionary methods are adopted and mimicked from nature while grid based methods search for optimality within a configuration space. Evolutionary approaches have the advantage of handling multi - objectives in path planning although convergence of such methods is not guaranteed in a finite time and one may end with sub - optimal solution. Local approaches are time implementation but solutions can get trapped in local minima. All path planning techniques are subjected to finding obstacle free paths in a Cspace with certain optimisation objectives.

The metric framework considers a two-dimensional space in which it places the objects. The objects are placed with precise coordinates. This representation is very useful, but is sensitive to noise and it is difficult to calculate the distances precisely. There are three main methods of map representations, i.e., free space maps, object maps, and composite maps.



[35] In order to perform MOGWO, two components were integrated to the single objective GWO algorithm. One was an archive responsible for storing non - dominated Pareto optimal solutions obtained. The second component is a leader selection strategy that assists to choose alpha, beta and delta as the leaders of the archive to update and replace the solutions. This is done by a roulette wheel method using a probability for each hypercube(segment) where the probability of deleting a solution is increased proportional to the number of solutions in the hypercube (segment). There is an archive controller which controls the solution from entering the archive when it is full. Third, a grid mechanism has been integrated to the GWO in order to improve the non-dominated solutions in the archive. The author concluded that the MOGWO is suitable for problems with continuous variables with less than 4 objectives.

The **MOEA/D** utilizes a fast non - dominated sorting technique. It starts with a random population and the individuals are grouped based on the non - dominated sorting method. The fitness of each individual is defined based on its non domination level. The second population is created by the selection, recombination and mutation operators. Both populations create a new big population. This new population is then sorted again by the non dominating approach. The higher the non - domination level, the higher priority to select as a new individual for the final population. The process of selecting non dominated individuals should be repeated until having a population with the same size of the initial population.

This paper proposes an **Multiple Objective Improved Grey Wolf Optimisation** for global path planning taking into the account of current effects.

3. Problem Formulation:

3.1 The USV Motion Model:

The six degrees of freedom in the mathematical model of an USV is studied to better understand the maneuvering behaviour in path planning problems [34]. Generally, within the path planning problem, the navigation of the USV can be treated as a rigid body motion on the horizontal surface in the form of three degrees of freedom (the surge, sway and yaw), thus neglecting heave, roll and pitch motions.

$$\begin{cases} m_{USV}(\dot{u} - vr - x_G r^2) = X & Surge \\ m_{USV}(\dot{v} + ur + x_G r^2) = Y & Sway \\ I_Z \dot{r} + m_{USV} x_G(\dot{v} + ur) = N & Yaw \end{cases}$$

3.2 Bounded Motion Area of USV:

Suppose the USV's path S consists of a sequence of linked elementary line segments si (i = 1,…, m). Following path S, USV navigates from the initial location (x0, y0) to the intended final position (xf , yf) in the presence of a set of obstacles Obs (Obs = {Obs_1, Obs_2,…, Obs_j,…, Obs_k}, j = 1, 2,…, k, and k is the number of obstacles). The obstacles including over-water buildings and submerged obstructions are represented as polygons(circles) on the horizontal plane.

The boundary of the motion area is known and is represented by Barea. Knowing the limit of the top, bottom, left and right channel dimensions, the area remaining subtracting the area of the obstacles is the Free Area (Area_Free) where the USV can navigate. The path generated must be restricted to this Free Area for a safe navigation of the USV.

$$S = \cup_{i=1}^{m} s_i \subset A_{rea\_free}$$

3.3 Effect of Currents for path planning for USV:

[3,21] Both fixed and time varying current distributions are taken for USV navigation. Fixed currents are mainly applied to navigate inland rivers, and the time-varying currents are used in the ocean. To accurately reflect the motion of the currents, time-varying currents are described by an eastward flowing jet, which can be depicted by a mathematical model with north-south directional meandering as follows.

$$\phi(x, y) = 1 - \tanh\left(\frac{y - B(t)\cos(k(x - ct))}{\left(1 + k^2 B(t)^2 \sin^2(k(x - ct))\right)^{1/2}} \right)$$

B(t) and k are the properly dimensionless amplitude and wave-number of the undulation in the stream function. B(t) can be represented as B(t) = B0+εcos(wt+β). Terms B0, ε, w, k, and c are adopted to illustrate the time-varying currents field that is updated at each integrated value of time.

Suppose components of the current velocity Vc in the directions of OX and OY in XOY coordinates are Vcx and Vcy, respectively. Then, at time t, vcx and vcy can be computed as

$$\begin{cases} v_{cx}(t) = -\dfrac{\partial \phi}{\partial y} \\ v_{cy}(t) = \dfrac{\partial \phi}{\partial x} \end{cases}$$

The effects of currents should be strengthened from the perspective of the direction and magnitude of the current velocity in USV path planning.
Suppose that, at S1, the velocity of the USV is V and the heading angle related to the direction of OX is θ. The effects exerted on the USV by currents would be evidently manifested in the velocity of the USV.

Suppose Vx and Vy are the velocities of the USV projected on the OX and OY directions; they are calculated as

$$\begin{cases} V_x = V\cos\theta + v_{cx} \\ V_y = V\sin\theta + v_{cy} \end{cases}$$

The motion of the USV is forward and toward the destination. Even under the severe condition that the USV travels along the reverse direction of the current, this work postulates that the USV could endure the potential negative effect brought by the current, and the below constraints should be satisfied

$$V + v_c \geq 0$$

3.4 Multi Objective Path Navigation Environment for USV:

The Path Planner aims to encompass three main objectives during the navigation process and they are as follows: (i) path length (ii) path smoothness (iii) path safety

(i) Shortest Path Length:
Generally, the shortest path distance can save work time and energy, which can enable USV to accomplish the task quickly. The distance objective function J1 is defined as

$$min \sum_{i=1}^{m} \sqrt{\left[(x_{i-1} - x_i)^2 + (y_{i-1} - y_i)^2\right]}$$

where path L is composed by several sequential line segments xi (i = 1, …, m) from starting point (xi-1, yi-1) to destination (xi, yi) in Cartesian coordinates.

(ii) Path Smoothness:

A smooth path can reduce turning vibration and strengthen maneuverability, which can enable USV to move smoothly and stably. The smoothness path objective function J2 can be defined as

$$min\sum_{i=1}^{m}\theta=\sum_{i=1}^{m}\left|atan2\left(\frac{y_{i+1}-y_i}{x_{i+1}-x_i}\right)-atan2\left(\frac{y_i-y_{i-1}}{x_i-x_{i-1}}\right)\right|$$

(iii) Path Safety:

During the navigation process, the USV should pass through navigable waters without colliding with any obstacles. To ensure the safety of the USV, it is critical to achieve the safest path by which the USV can move freely from its start position to the final position.

Because obstacles are represented by polygons, we propose the use of minimum circles that just cover the obstacles to embody the path safety degree.

Suppose that the length of the USV is Lusv, that the set of the circles corresponding to k obstacles is {(xccj, yccj),rccj}, where k is the number of Obs, j = 1, 2,…, k, and that (xccj, yccj) and rccj are the center and the radius of the circle, respectively.

The real distance, the least distance, and the lower limit of the maximum distance between Obs_j and S are denoted as dreal_j, dsafe_minj and dsafe_maxj, respectively. Then, when comes to the path S, the safety degree of S related to the jth obstacle named Dsafej is

$$min\sum_{j=1}^{m}D_{safe}=\begin{cases}1 & d_{r\_j}<d_{safe\_\min j}\\ 0 & d_{r\_j}\geq d_{safe\_\max j}\\ \dfrac{d_{r\_j}-d_{safe\_\min j}}{d_{safe\_\max j}-d_{safe\_\min j}} & other\end{cases}$$

The boundaries of the above objectives are **0 ≤ L0 < ∞, 0 ≤ θ0 ≤ 60◦ and 0 ≤ DSafe ≤ k**, where k is the number of obstacles and gates.

4. Solution: Overview of the Grey Wolf Optimizer Algorithm

The GWO was a heuristic developed in 2014 inspired by the social hierarchy of grey wolves. It is a swarm intelligence algorithm which is inspired from the leadership and hunting mechanism of grey wolves in nature.

[50] GWO is a heuristics inspired from the leadership hierarchy and hunting mechanism of grey wolves in nature and has been successfully applied for solving economic dispatch problems [37], feature subset selection [38], optimal design of double layer grids [39], time forecasting [40], flow shop scheduling problem [41], optimal power flow problem [42], and optimizing key values in the cryptography algorithms [43].

A number of variants are also proposed to improve the performance of basic GWO that include binary GWO [44], a hybrid version of GWO with PSO [45], integration of DE with GWO [47], and parallelized GWO [47,48].

In the hierarchy of GWO, alpha is considered the most dominating member among the group. The rest of the subordinates are beta and delta which help to control the majority of wolves in the hierarchy that are considered as omega. These wolves are of lowest ranking in the hierarchy.
The mathematical model of hunting mechanism of grey wolves consists of the following:
(i)Tracking, chasing, and approaching the prey.
(ii)Pursuing, encircling, and harassing the prey until it stops moving.
(iii)Attacking the prey.

(i) Encircling:

Grey wolves encircle the prey during the hunt which can be mathematically written as

$$\vec{D} = \left|\vec{C} \cdot \vec{X_p}(t) - \vec{X}(t)\right|,$$

$$\vec{X}(t+1) = \vec{X_p}(t) - \vec{A} \cdot \vec{D},$$

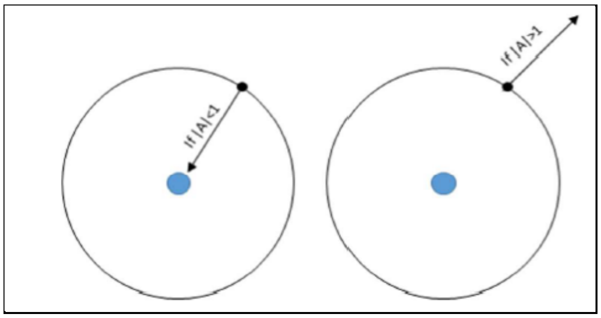
where t indicates the current iteration, A indicating discrimination weight coefficent and C indicating random mutation coefficient are vectors, Xp is the position vector of the prey, and X indicates the position vector of a grey wolf. The vectors A and C are calculated as follows:

$$A_w^d = 2e{\cdot}rand_1 - f$$
$$C_w^d = 2{\cdot}rand_2$$

where components of 'f' are linearly decreased from 2 to 0 over the course of iterations and rand1 and rand2 are random vectors in [0,1].

(ii) Hunting:

Hunting of prey is usually guided by alpha and beta, and gamma will participate occasionally. The best candidate solutions, that is alpha, beta and gamma have better knowledge about the potential location of prey. The other search agents omega update their positions according to the position of three best search agents. The following formulas are proposed in this regard:



$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|,$$
$$\vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|,$$
$$\vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right|,$$
$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \left(\vec{D}_\alpha\right),$$
$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \left(\vec{D}_\beta\right),$$
$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \left(\vec{D}_\delta\right),$$
$$\vec{X}(t+1) = \frac{\vec{X}_1(t) + \vec{X}_2(t) + \vec{X}_3(t)}{3}.$$

(iii) Attacking Prey

In order to mathematically model for approaching the prey, we decrease the value of a. The fluctuation range of A vector is also decreased by a. A vector is a random value in the interval [-a,a] where a is decreased linearly from 2 to 0 over the course of iterations. When random values of A are in [-1,1], the next position of a search agent can be in any position between its current position and the position of the prey. The value |A|<1 forces the wolves to attack the prey.

4.1 Improved GWO:

1. Non Linearity in 'f'

[51] The author introduces a very important change, a nonlinear convergence factor that helps it escape the local optimum solution as follows:

The encirclement size is mainly determined by A, which is further influenced by the linearly decreasing variable f. In the first half of iteration, |A|>1 means that the global search dominates the process. In the second half of iteration, |A|<1 signifies that the local search prevails. When it comes to complex optimization cases, however, the local optimal problem is very common. Hence the global search ability should be further improved in order to escape from the local optimal solution. Therefore the nonlinear convergence factor is used to replace

$$f = 2 - 2\left(\frac{1}{e-1} \times \left(e^{t/t_{\max}} - 1\right)\right)$$

At the preliminary stage, f will decrease with a much slower speed, and consequently the global search process will keep for a longer time. At the latter stage, however, it will decrease much faster in order to shrink the encirclement size.

2. Introducing Chaos to the Parameter 'C'

The variable C in GWO adds weight to the prey position, which in turn helps in defining the wolf's position. A better value of C governs the optimization process toward global optimum. In the proposed method, C is chaotically altered by replacing rand2 with a chaotic variable normalized between 0 and 1. One-dimensional chaotic map is used for adding the chaos in the optimization algorithm. For the proposed method, the chaotic map used is: Sinusoidal map generating sequence between 0 and 1.

$$r_{k+1} = f \cdot r_k^2 \cdot \sin(\pi r_k)$$

where the initial state random values are between 0.6 and 0.8 depending on the number decision variables and f is constant having the value 2.3. The sinusoidal map is used for generating the chaos in the proposed method, because of its periodic nature and the requirement of the variable C to generate sequence between 0 and 1.

3. Individual Memory in addition to the Social Group Learning

[51] The author, inspired by Traditional PSO, introduces individual memory into the equation to update the position of the wolves in addition to the group social learning that already exists.

$$U_w^d(t+1) = b_1 \cdot \frac{1}{3} \sum_{j=\alpha,\beta,\delta} U_{w,j}^d(t+1) + b_2 \cdot rand_3 \cdot (U_{w,\text{best}}^d - U_w^d(t))$$

Where rand3 is the random value in the range [0,1] , b1 and b2 are the learning factors of social learning and individual memory.

4.2 Multi - objective IGWO:

[35] The author proposes the novel Multi objective GWO inspired from the MOPSO [52]. The implementation of MOGIWO is to be compared with the two most popular optimization techniques ie. MOEA/D and MOPSO.

The author integrates an external archive to choose the non dominating solutions of the Pareto Optimal Front which consists of satisfying the following four conditions:

- Pareto Dominance
- Pareto Optimality
- Pareto Optimal Set - set including non dominated solutions
- Pareto Optimal Front - set containing the the corresponding objective values of Pareto Optimal Solutions in Pareto Optimal Set

[55] The optimal Solution of the multiobjective optimization can be obtained from the Pareto Optimal Set.

Multiobjective optimization for a minimization problem with d - dimensional decision vectors and h objectives is given by

$$Minimize\ F(P) = (f1(x_j, y_j),\ f2(x_j, y_j),\ f3(x_j, y_j))\ subject\ to\ (x_j, y_j)\ \varepsilon\ (x_l, y_l), (x_U, y_U)$$

F(x,y) is the objective function vector, XL,YL and XU,YU are the lower and upper bound constraints of the agent range.

Values of the 3 objectives chosen are normalised for every solution in the archive, finding the max and min values of every objective and transformed into values ranging from 0 and 1.

Using a Preference Set (Pset), with weights given to each objective randomly, the best solution is having the minimal normalised total, the best path is chosen from the external archive and final costs and final coordinates.

4.3. Performance Metrics:

The performance metrics used are IGD (Inverted Generational Distance) to measure convergence, the Spacing (SP) and Maximum Spread (MS) are employed to quantify and measure the coverage.

IGD: [60] IGD defines the closeness of the solution set of an applied algorithm from the true Pareto optimal solution set. True Pareto front is obtained via comparing the Pareto optimal solutions of each applied algorithm. Lower the value of IGD, closer will be the obtained solution set from the true Pareto front. Lower value of IGD signifies better performance of the applied multi-objective algorithm. IGD can be evaluated as

$$\mathrm{IGD} = \frac{\sqrt{\sum_{i=1}^{Z} A_i^2}}{Z}$$

where Z indicates total number of non-dominated solution and Ai is calculated as:

$$A_i = \sqrt{\left(F_{1_i} - F_{1_i}^{TP}\right)^2 + \left(F_{2_i} - F_{2_i}^{TP}\right)^2}$$

F1i and F2i are the ith solution of the objective function F1 and F2, respectively and F^TP,1i and F^TP,2i are the corresponding closest obtained Pareto solution in the true Pareto set.

Spacing: [60]It defines the distribution of the solution of a particular Pareto set throughout the non-dominated solutions found so far. The SPACING metric can be evaluated as

$$S^P = \sqrt{\frac{1}{Z-1}\sum_{i=1}^{Z}(\bar{a}-a_i)^2}$$

where a¯ indicates normalized value of all ai and ai can be calculated as

$$a_i = min_o\left(\left|F_{1_i}(\mathbf{x}) - F_{1_o}(\mathbf{x})\right| + \left|F_{2_i}(\mathbf{x}) - F_{2_o}(\mathbf{x})\right|\right)$$

where i, o = 1,2,3…Z.

A lower value of the SPACING metric indicates that the solution of the Pareto front is more prone to be equidistantly spaced. The purpose of this metric is to have clearer insight about the solution spread. Smooth and uniform distribution of solution is preferred for a true Pareto front.

Maximum Spread: The MAXIMUM SPREAD is calculated as

$$MS = \sqrt{\sum_{r=1}^{of}(\max(D(q_r, b_r)))}$$

where D is the euclidean distance function, qr is the maximum value of the rth objective function, br is the minimum value of the rth objective function.

5. Implementation - Algorithm: MOIGWO

Input: Length of USV,USV velocity, USV heading angle, Fixed/Time Varying Currents, Starting Point (x0,y0), End Point - Waypoint (xf,yf), Obs, Environment Boundaries, WaveCurrent $\Phi(x, y)$, nVar - number of decision variable or points between the start point and waypoint

Process:

Step 1	Modelling the topological environment in 2D configuration Space which includes the position and orientation of gates, shapes of obstacles, the USV start and final position coordinates.
Step 2	Formulate the mathematical model of the USV path planning problem taking into account the boundary constraint, angle constraint of 60◦ and velocity constraint taking into the account the current effects.

Step 3	Initialise the number of Grey Wolves, its velocity, x and y coordinates in the following manner: x coordinates - find the range between end point x coordinate and start point x coordinate, divide the range into equal parts depending on nVar and initialize the Grey Wolves. y coordinates - the first position is initialised with respect to the length of the USV and the other positions are initialised between the maximum and minimum range which are calculated by taking the difference of start point and end point y coordinates.
Step 4	At iteration = 0, check all the constraints and calculate the fitness of the Grey Wolves and update the Best Position and Best Cost of each GreyWolf respectively.
Step 5	Find the non dominating solutions and fill the external archive with those solutions after iteration =0
Step 6	Iter = Iter +1. Non linearity in f and chaotic factor is initialised.
Step 7	The three best solutions of the archive are selected and Alpha, Beta, Delta wolves are initialised.
Step 8	The position of all the wolves are updated using social group learning and individual memory.
Step 9	Obtain the values of the multiple objectives if all constraints mentioned above are satisfied by the Grey Wolf, update the best position and best cost of each Grey Wolf.
Step 10	Iterate for every Grey Wolf agent in the above mentioned manner, store all the non dominated feasible solutions into the external archive, update the archive and increase the loop counter.
Step 11	Go back to step 4 till it is less than the total number of iterations.
Step 12	Find maximum and minimum of every objective value in the archive and normalise the costs and identify the best path using the Pset.
Step 13	Guide the USV to the target position by the optimal path selected after every time interval from the starting point via waypoints to the final end point.

Output: (x,y) coordinates at every time interval of all intermediate points, cost of every objective between waypoints, (min,max,range,st.dev, mean) values of every objective, S - path segments

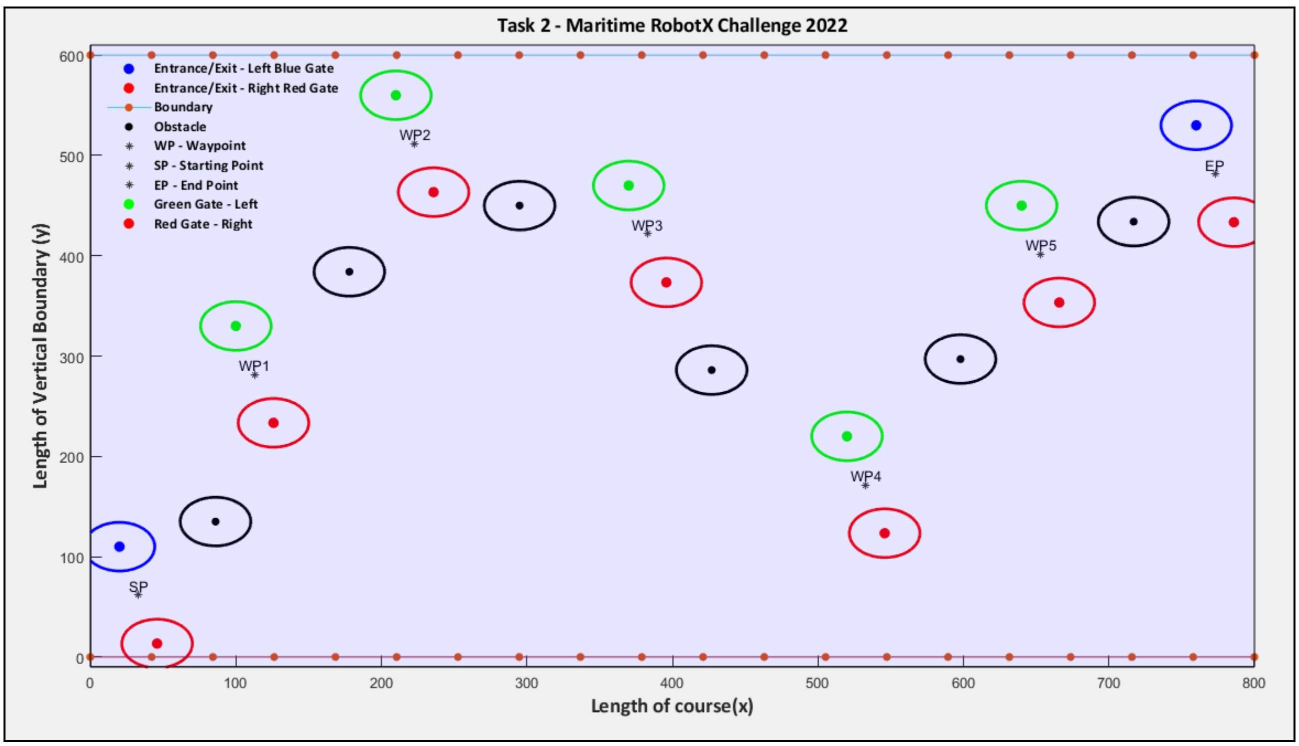
6. Simulation Analysis

Simulation Parameters:

All the experiments were performed on **Matlab R2020a, Windows 10 Intel(R) Core™ i7 - 8550-U @1.80 GHz, 8GB DDR4 Ram**

The following table indicates the coordinates of the gates and obstacles in the map that was used to run the forthcoming experiments for selection of parameters. The course dimensions are approximately **80m x 60m**, the dimensions of obstacles, boundaries and gates were taken as given before as part of Maritime RobotX Challenge.. For better visualization, all the values were converted to **decimeters**.

Path safety is in degrees. Distance between the gates is taken as 100 dm. The solid circles indicate the diameter of the obstacles and gates while the outer circle is the diameter of including the half the length of the actual USV which is 24.25 dm.



	X coordinate	Y coordinate
EntranceBlue Gate	20	110
EntranceRed Gate	45.8819045102521	13.4074173710932
ExitBlue Gate	760	530
ExitRed Gate	785.881904510252	433.407417371093
Obstacle - 1	86	135
Obstacle - 2	178	384
Obstacle - 3	295	450
Obstacle - 4	427	286
Obstacle - 5	598	297
Obstacle - 6	717	434
Green Gates - 1	100	330
Green Gates - 2	210	560
Green Gates - 3	370	470
Green Gates - 4	520	220
Green Gates - 5	640	450
Red Gates - 1	125.881904510252	233.407417371093
Red Gates - 2	235.881904510252	463.407417371093
Red Gates - 3	395.881904510252	373.407417371093
Red Gates - 4	545.881904510252	123.407417371093
Red Gates - 5	665.881904510252	353.407417371093

The following are the coordinates that the USV was made to attain to achieve optimal path in shortest time:

Starting Point	32.940952255126	61.7037086855466
End Point	772.940952255126	481.703708685547
Waypoint - 1	112.940952255126	281.703708685547
Waypoint - 2	222.940952255126	511.703708685547
Waypoint - 3	382.940952255126	421.703708685547
Waypoint - 4	532.940952255126	171.703708685547
Waypoint - 5	652.940952255126	401.703708685547

6.1 Selection of Global Path Testing Parameters

These parameters are taken as the constants for all the experiments unless otherwise mentioned.

Pset = [0.3,0.3,0.4], Lusv = 24.25 dm, alpha = 0.1 (Grid inflation parameter), nGrid = 10 (number of grids per dimension), beta =4 (Leader selection Pressure Parameter), gamma = 2 (Extra Repository Member to be deleted), fixed wave current (East to West)= 3m/s, USV velocity = 5m/s

Boundary of the course: xmax = endpoint(x), xmin = startpoint(x), ymax = endpoint(y)+Lusv, ymin = endpoint(y) - Lusv

All simulations were run for 5 times. Obj 1 - Minimum Path length, Obj 2 - Minimum Path Smoothness, Obj 3 - Minimum Path Safety, Total Runtime (in secs) Here the external archive size refers to the number of pareto paths obtained.

Exp 1: Changing No of Grey Wolves for fixed Time iterations for 3 objectives for fixed current direction
No of time iterations = 50, Archive Size = 20, nVar = 7

No of GreyWolves = 10	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1469.369412	832.4760688	0	91.9558894
Max	1487.206913	948.0896408	0	100.510441
Min	1453.552038	706.6156618	0	91.9558894
Std Dev	13.29673859	78.72640219	**0**	8.56383514

No of GreyWolves = 20	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1461.866135	850.2482495	0.278926663	201.97
Max	1476.106587	964.0258327	0.837629016	221.21
Min	1451.011708	759.6075464	0	192.14
Std Dev	9.83577468	76.95536786	0.352952048	10.643

No of GreyWolves = 30	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1443.78405	684.5257895	0.17906	267.8014
Max	1454.41557	712.230518	0.8953	308.1341
Min	1437.866342	620.699043	0	227.0097
Std Dev	**6.272522733**	**34.28661641**	0.35812	**26.36642**

No of GreyWolves = 40	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1436.573898	684.2616423	0	401.2122
Max	1442.859054	782.4599027	0	421.5859
Min	1422.85843	631.4715093	0	359.137
Std Dev	7.701041525	53.99676465	**0**	22.38292

Inference: The standard deviation is least for 2 objectives when the number of Grey wolves is **30** showing that the simulations are closer.

Exp 2: Changing No of time iterations for fixed number of Grey Wolves for 3 objectives for fixed current direction

No of Grey Wolves = 30, Archive Size = 20, nVar = 7

No of Time iter = 30	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1454.950961	759.8929286	0	254.6587
Max	1486.568206	832.9842483	0	268.7477
Min	1442.748911	694.8383928	0	243.7754
Std Dev	16.34985325	47.03865215	**0**	9.303137

No of Time iter = 50	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1443.78405	684.5257895	0.17905995	267.8014
Max	1454.41557	712.230518	0.89529975	308.1341
Min	1437.866342	620.699043	0	227.0097
Std Dev	**6.272522733**	**34.28661641**	0.3581199	**26.36642**

No of Time iter = 70	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1454.516384	737.2045198	0	260.2438
Max	1474.060956	804.6727934	0	296.5914
Min	1435.182528	666.7485128	0	227.3103
Std Dev	13.72019109	47.66302412	**0**	24.01019

No of Time iter = 90	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1443.583985	676.4686513	0.2	269.6999
Max	1476.764867	894.5798935	1	309.1468
Min	1423.469766	568.8183289	0	243.6985
Std Dev	20.8376946	116.7391862	0.4	22.79529

Inference: The standard deviation is least for 2 objectives when the number of iterations is **50** showing that the simulations are closer.

Exp 3: Archive Size for fixed time iterations and fixed number of Grey Wolves for 3 objectives for fixed current direction

No of Grey Wolves = 30, No of Time iterations = 50, nVar = 7

Archive Size = 20	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1443.78405	684.5257895	0.17905995	267.8013748
Max	1454.41557	712.230518	0.89529975	308.134107
Min	1437.866342	620.699043	0	227.009715
Std Dev	**6.272522733**	**34.28661641**	0.3581199	26.36642417

Archive Size = 30	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1444.706161	698.1877681	0	229.3234094
Max	1466.406125	781.396202	0	248.838065
Min	1433.891968	642.9366777	0	214.197311
Std Dev	11.24360314	58.62313123	**0**	**11.75131393**

Inference: The standard deviation is least for 2 objectives when the Archive Size is 20 however when the Archive Size is 30 the important objective Path Safety is satisfied better and total runtime is also lesser..

Exp 4: No of decision variables between start and end point for 3 objectives for fixed current direction

No of Grey Wolves = 30, No of Time iterations = 50, Archive Size = 30

nVar = 5	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1436.013566	613.4431222	0	18.0922504
Max	1446.207728	693.355304	0	20.190607
Min	1425.153451	515.179976	0	15.552758
Std Dev	7.557701603	59.37772363	0	1.563985931

nVar = 6	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1433.862452	629.8647125	0.281304712	46.415648
Max	1444.859037	729.2553075	0.851291551	50.593324
Min	1427.631361	560.3226674	0	41.104821
Std Dev	6.418925873	54.91396777	0.357020499	3.42556841

nVar = 7	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1444.706161	698.1877681	0	229.3234094
Max	1466.406125	781.396202	0	248.838065
Min	1433.891968	642.9366777	0	214.197311
Std Dev	11.24360314	**58.62313123**	**0**	**11.75131393**

Inference: The standard deviation is least for 2 objectives when the nVar =7 considering Path Safety to be the most important objective. Though the total runtime is more when nVar =7, the accuracy of the paths obtained was substantially higher and the runtime between each waypoint is around 40 secs.

Hence the final set of parameters selected were as follows:

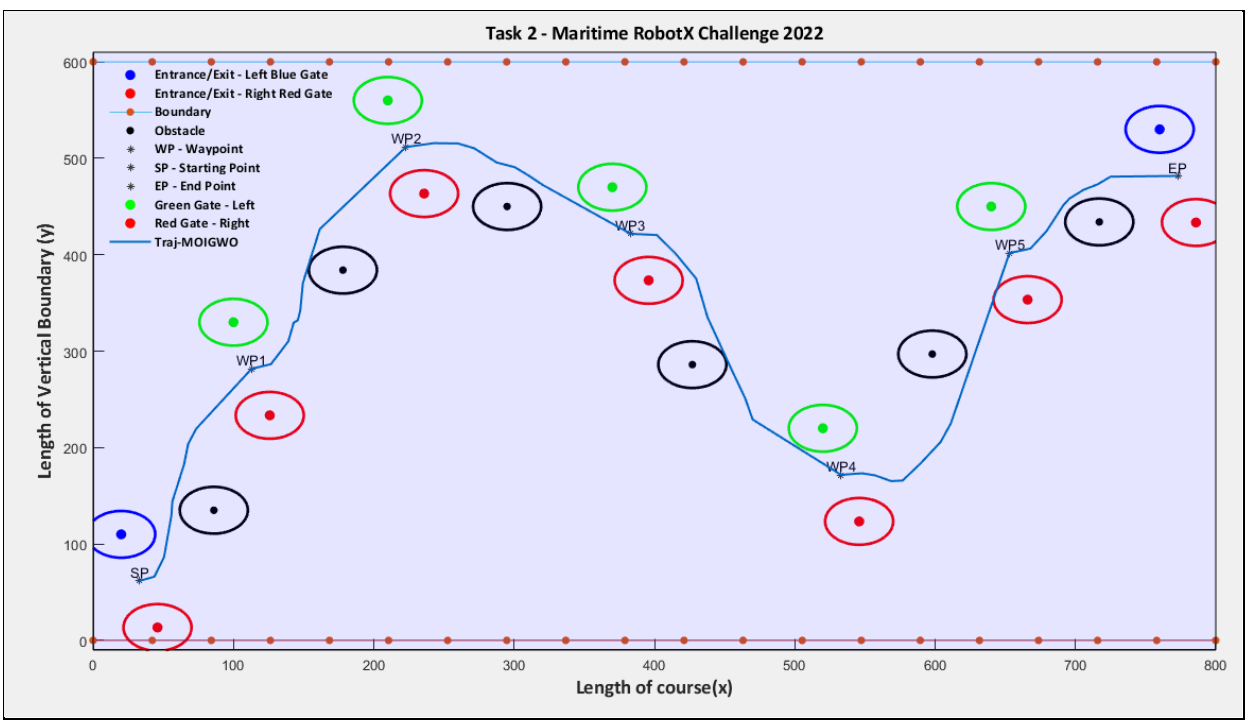
No of Grey Wolves = 30, No of time Iterations = 50, Archive Size = 30, nVar = 7

6.2 Simulation Analysis

Exp 1: Finding the most optimal path for 3 objectives for Fixed Current direction

Paths	Obj1	Obj2	Obj3	Total Runtime
Path 1	**1433.891968**	654.0700168	0	232.698225
Path 2	1440.901196	756.914175	0	221.007656
Path 3	1466.406125	781.396202	0	**214.197311**
Path 4	1439.630968	655.6217691	0	248.838065
Path 5	1442.700546	**642.9366777**	0	229.87579

Of the 30 Pareto paths generated, the path with the least Normalised Cost was selected in each simulation. Best Overall Path obtained was **Path 3**.



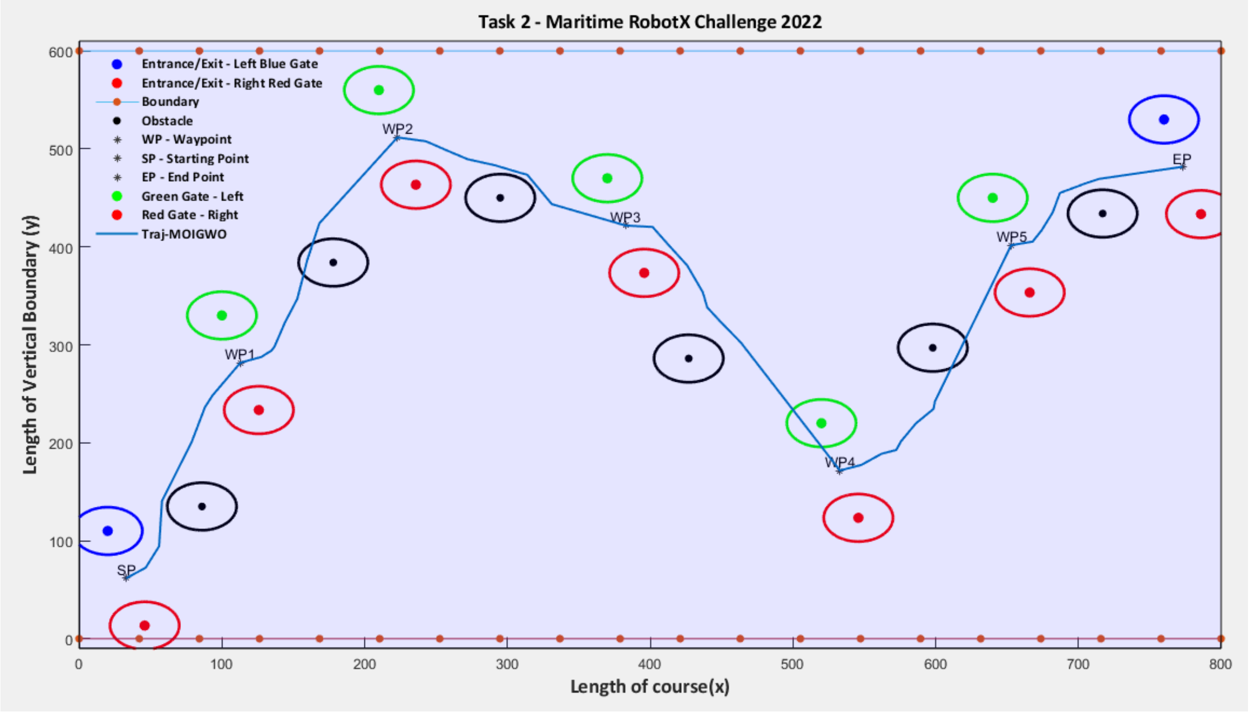
Inference: Due to the use of waypoints, the best path can be modified by using the shorter path segments obtained from the different simulation. The code is working perfectly and an optimal path is being generated every simulation.

For all the following 2 objective problems, Pset = [0.5,0.5].

Exp 2: Finding the most optimal path for 2 objectives - Shortest Path and Path Smoothness for Fixed Current direction

Paths	Obj1	Obj2	Total Runtime
Path 1	1430.315765	688.107779	**236.683617**
Path 2	1429.42969	698.0640689	245.731092
Path 3	**1425.062348**	**671.7158227**	282.954998
Path 4	1429.715687	702.0469473	273.756961
Path 5	1432.983947	758.7360099	287.732228

Of the 30 Pareto paths generated, the path with the least Normalised Cost was selected in each simulation Best Overall Path obtained was **Path 3**.

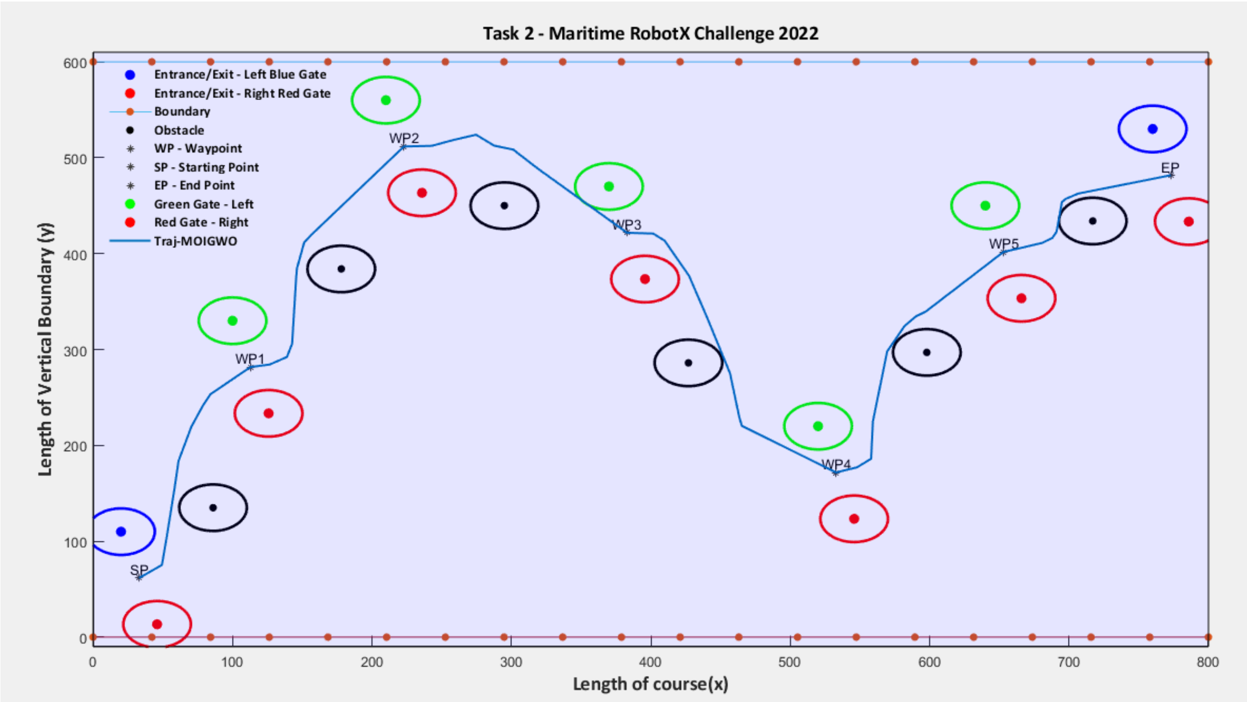


Inference: The best overall path has the least cost in both the objectives Shortest Path Length and Minimum Angle or Path Smoothness with optimal safety due to constraints in place.

Exp 3: Finding the most optimal path for 2 objectives - Path Smoothness and Path Safety for Fixed Current direction

Paths	Obj2	Obj3	Total Runtime
Path 1	729.0242376	0	257.450505
Path 2	736.5193467	0	238.456606
Path 3	**678.5470381**	0	292.005963
Path 4	693.6865937	0	253.28579
Path 5	764.6015741	0	**220.042236**

Of the 30 Pareto paths generated, the path with the least Normalised Cost was selected in each simulation. Best Overall Path obtained was **Path 1**.

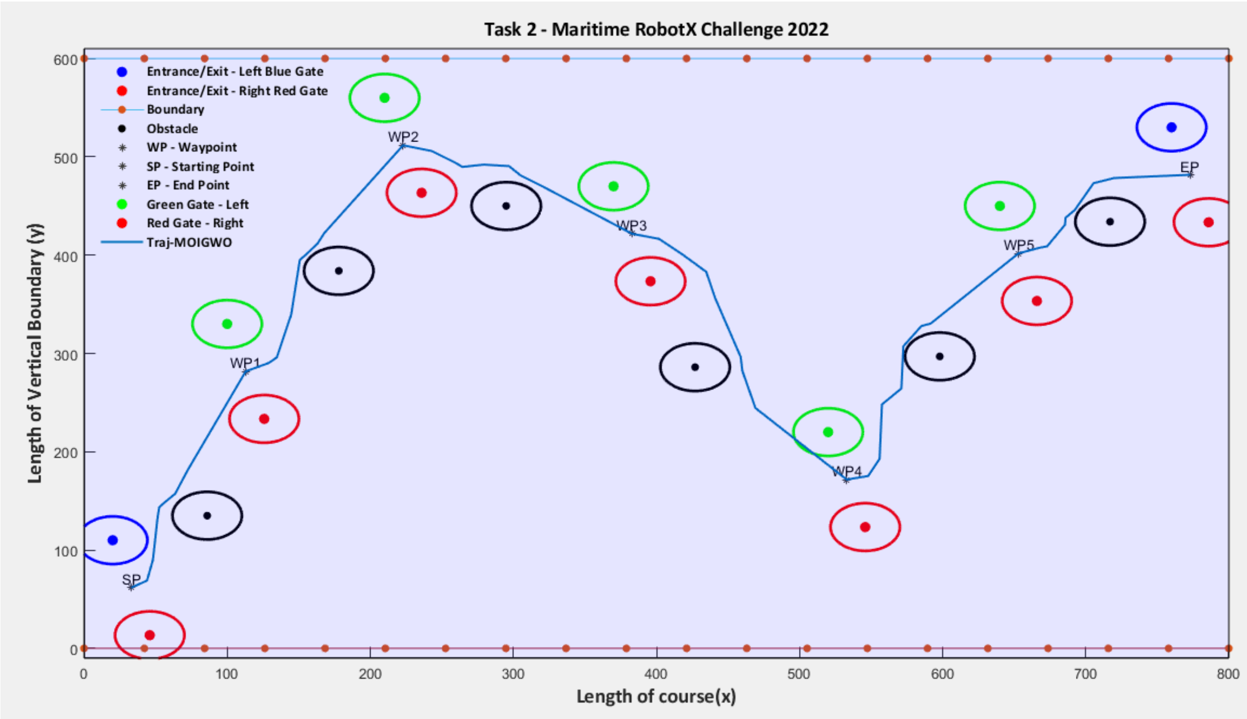


Inference: The best overall path has the least cost in both the objectives Minimum Angle or Path Smoothness and Path Safety with optimal Path length satisfying all the constraints in place.

Exp 4: Finding the most optimal path for 2 objectives - Shortest Path Length and Path Safety for Fixed Current direction

Paths	Obj1	Obj3	Total Runtime
Path 1	1451.144476	0	244.74206
Path 2	**1424.457655**	0	248.458089
Path 3	1440.907068	0	240.819269
Path 4	1443.34806	0	239.037773
Path 5	1443.808985	0	**233.561624**

Of the 30 Pareto paths generated, the path with the least Normalised Cost was selected in each simulation. Best Overall Path obtained was **Path 4**.



Inference: The best overall path has an optimal cost in both the objectives Shortest Path Length and Path Safety and is relatively smooth satisfying all the constraints.

Exp5: Testing versatility of the proposed algorithm for 5 random maps by changing the angles between gates with 3 angles (-15◦, 0◦ , 15◦), changing the selection of gates and number of obstacles randomly.

Map1 Coordinates	**Map2 Coordinates**	**Map3 Coordinates**	**Map4 Coordinates**	**Map5 Coordinates**
EntranceBlue Gate: (20,110) EntranceRed Gate: (20,10) ExitBlue Gate: (760,530) ExitRed Gate: (785.8819045, 433.4074174) Obs: (86,135), (178,384), (295,450), (427,286), (598,297), (717, 434) GreenGates: (210, 560), (370, 470), (520,220), (640,450) RedGates: (210,460), (370,370), (494.1180955, 123.4074174), (640,450) Starting Point: (20,60) End Point: (772.9409523, 481.7037087) Waypoints: (210,510), (370,420), (507.0590477, 171.7037087), (640, 400)	EntranceBlue Gate: (20,110) EntranceRed Gate: (20,10) ExitBlue Gate: (760,530) ExitRed Gate: (734.118095489748, 433.407417371093) Obs: (86,135), (178,384), (295,450), (427,286), (598,297), (717, 434) GreenGates: (210, 560), (370, 470), (640,450) RedGates: (184.118095489748, 463.407417371093), (395.881904510252, 373.407417371093), (665.881904510252, 353.407417371093) Starting Point: (20,60) End Point: (747.059047744874, 481.703708685547) Waypoints: (197.059047744874, 511.703708685547), (382.940952255126, 421.703708685547), (652.940952255126, 401.703708685547) (640, 400)	EntranceBlue Gate: (20,110) EntranceRed Gate: (45.8819045102521, 13.4074173710932) ExitBlue Gate: (760,530) ExitRed Gate: (760,430) Obs: (86,135), (178,384) GreenGates: (100, 330), (210, 560), (370, 470), (520, 220) RedGates: (125.881904510252, 233.407417371093) (210, 460), (395.881904510252, 373.407417371093), (520, 120) Starting Point: (32.940952255126, 61.7037086855466) End Point: (760, 480) Waypoints: (112.940952255126, 281.703708685547), (210, 510), (382.940952255126, 421.703708685547), (520, 170)	EntranceBlue Gate: (20,110) EntranceRed Gate: (20,10) ExitBlue Gate: (760,530) ExitRed Gate: (785.881904510252, 433.407417371093) Obs: (86,135), (717, 434) GreenGates: (370, 470), (640,450) RedGates: (370,370), (665.881904510252, 353.407417371093) Starting Point: (20, 60) End Point: (772.940952255126, 481.703708685547) Waypoints: (370, 420), (652.940952255126, 401.703708685547)	EntranceBlue Gate: (20,110) EntranceRed Gate: (20,10) ExitBlue Gate: (760,530), ExitRed Gate: (785.8819045,433.4074174) Obs: (86,135), (178,384), (295,450), (427,286), (598,297), (717, 434) GreenGates: (100, 330), (520, 220), (640,450) RedGates: (125.881904510252, 233.407417371093), (520, 120), (665.881904510252, 353.407417371093) Starting Point: (20, 60) End Point: (772.940952255126, 481.703708685547) Waypoints: (112.940952255126, 281.703708685547) (520, 170), (652.940952255126, 401.703708685547)

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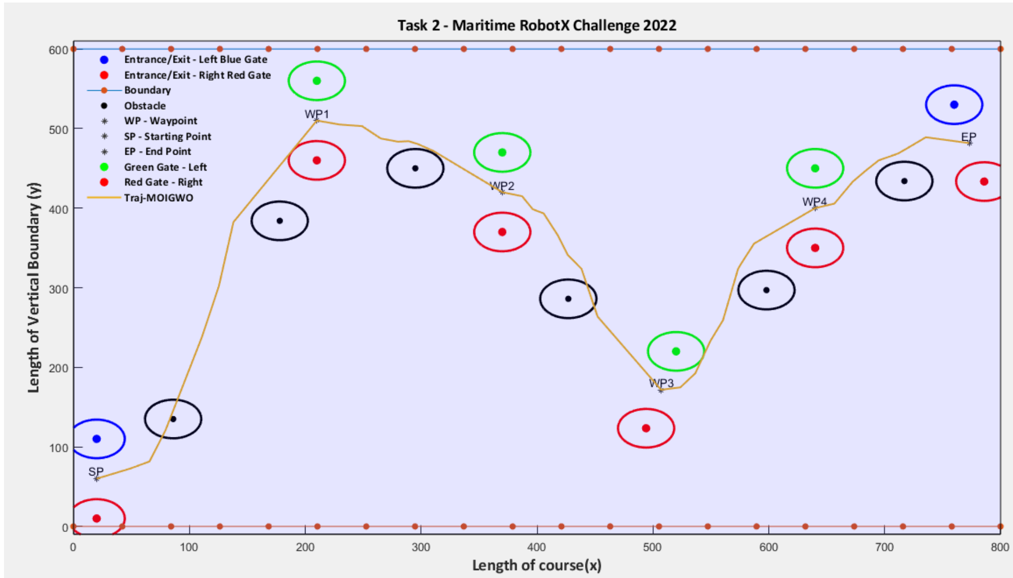
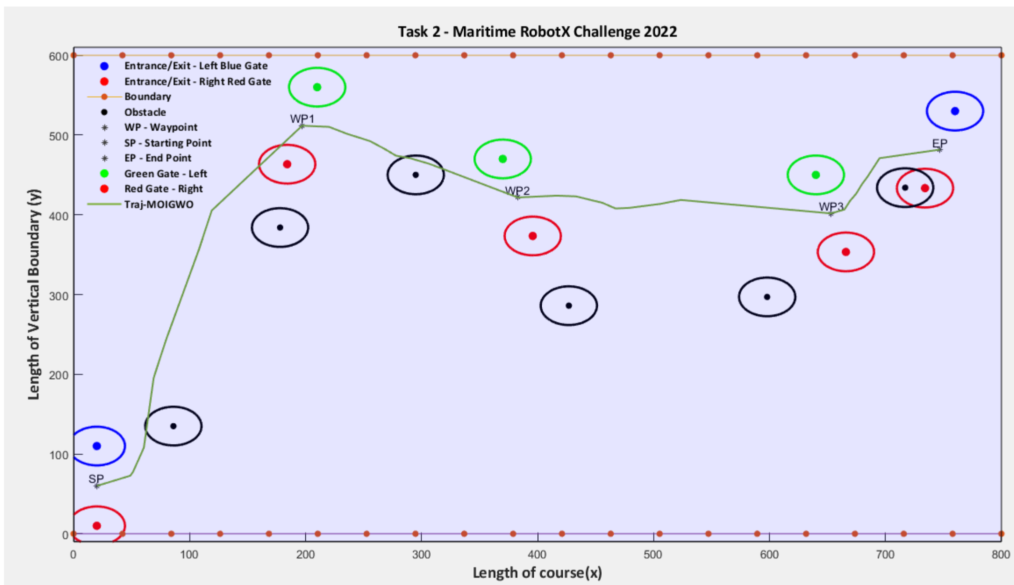
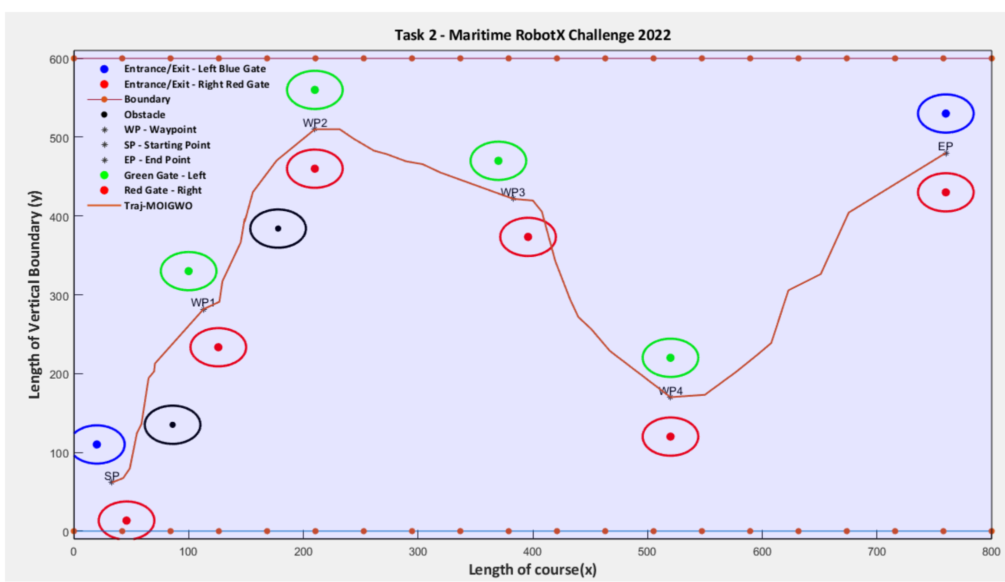
Path for Map1:



Path for Map2:



Path for Map3:



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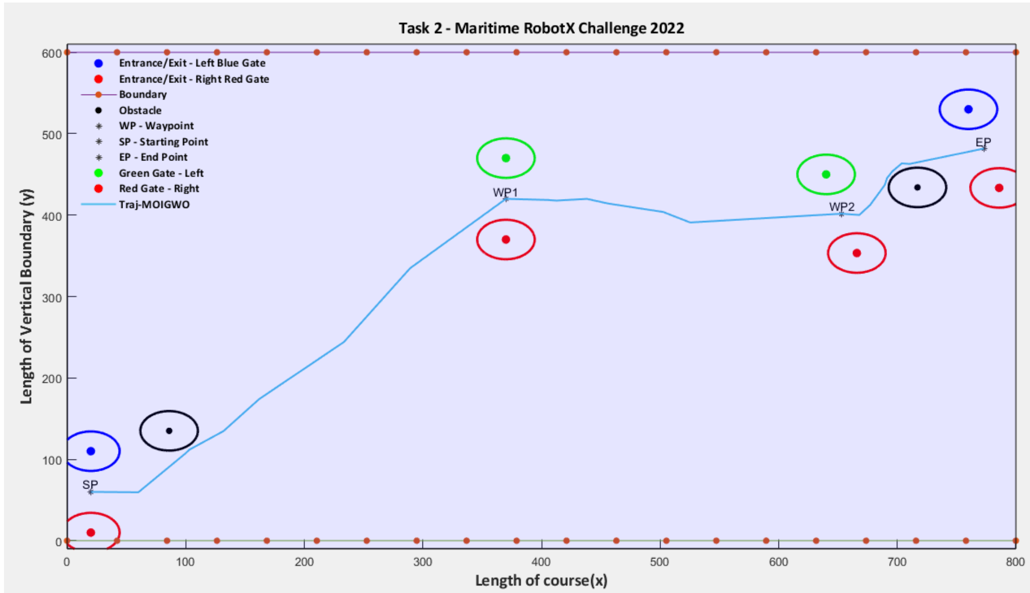
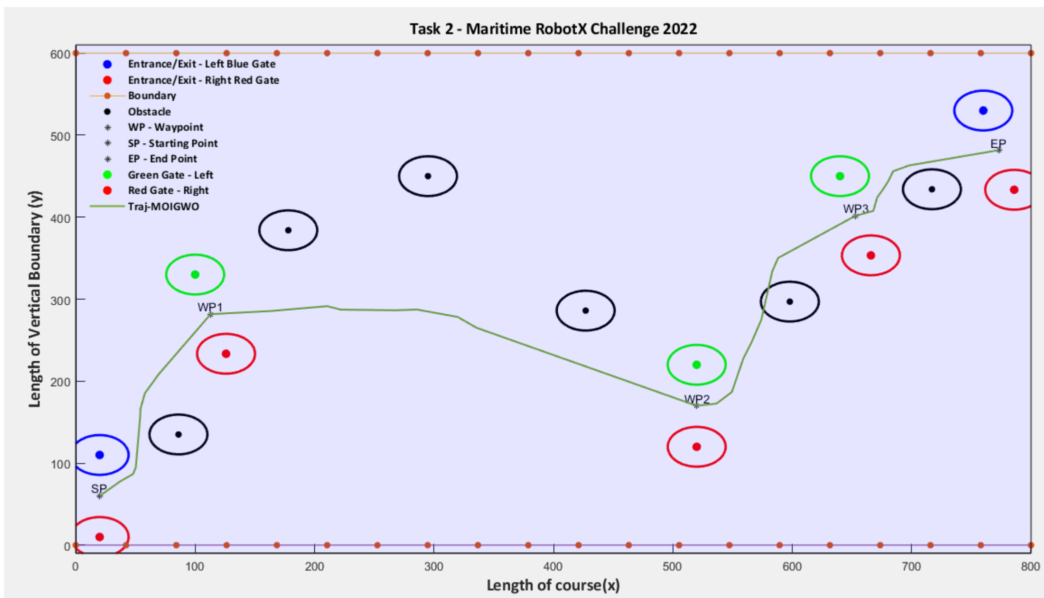
Path for Map4:



Path for Map5:



Of the 30 Pareto paths generated, the path with the least Normalised Cost was selected in each simulation using a Pset = [0.3,0.3,0.4]

The corresponding cost values are as follows:

	Map 1	Map 2	Map 3	Map 4	Map 5
Obj 1	1442.47963	1126.686587	1414.51786	967.6580411	1133.543645
Obj 2	645.061158	409.1572683	686.4035856	402.7965989	458.7679404
Obj 3	0	0	0	0	0
Total Runtime	241.265076	160.0069	132.444128	59.665393	157.16944

Inference: The Improved Grey Wolf algorithm proposed can be seen to function very accurately in 80% of the test cases in 1 simulation satisfying all the constraints and obtaining the most optimal path taking into consideration all the three objectives indicating its superior versatility to different courses and locations of obstacles and gates from the start point to end point via waypoints.

Exp 6: Comparison of costs using 5 simulations for MOIGWO, MOGWO and MOEAD/D for fixed current

Parameters:

MOIGWO, MOGWO - No of Grey Wolves = 30, T max = 50, Archive Size = 30, nVar =7, Pset = [0.3,0.3,0.4], Lusv = 24.25 dm, alpha = 0.1 (Grid inflation parameter), nGrid = 10 (number of grids per dimension), beta =4 (Leader selection Pressure Parameter), gamma = 2 (Extra Repository Member to be deleted), fixed wave current = 3m/s, USV velocity = 5m/s

MOEA/D - No of subproblem (nPop) = 30, Archive Size = 30, Tmax = 50, crossover_parameter (gamma) = 0.5, nVar =7, Pset = [0.3,0.3,0.4], Lusv = 24.25 dm, fixed wave current = 3m/s, USV velocity = 5m/s

Boundary of the course: xmax = endpoint(x), xmin = startpoint(x), ymax = endpoint(y)+Lusv, ymin = endpoint(y) - Lusv

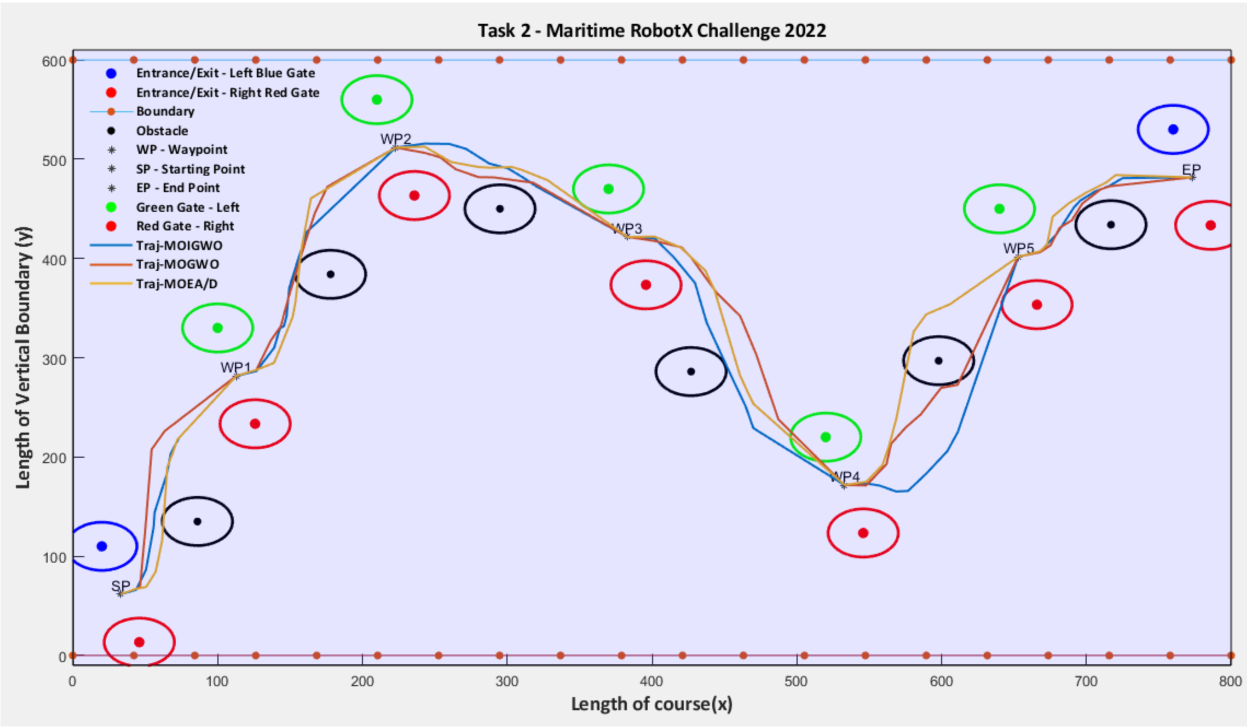
Of the 30 Pareto paths generated, the path with the least Normalised Cost was selected in each simulation.

MOIGWO	Obj 1	Obj 2	Obj 3	Total Runtime
Average	**1444.706161**	**698.1877681**	**0**	**229.3234094**
Max	1466.406125	781.396202	0	248.838065
Min	1433.891968	642.9366777	0	214.197311
Std Dev	11.24360314	**58.62313123**	**0**	11.75131393

MOGWO	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1446.680128	787.6632978	0	256.4968
Max	1462.013713	891.4487336	0	272.9811
Min	1435.303964	658.536547	0	242.4756
Std Dev	**9.316507842**	79.02079514	0	**11.69006**

MOEA/D	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1448.941309	820.1720945	0.182070859	252.0089472
Max	1470.003387	1063.00926	0.910354294	279.887547
Min	1423.651419	740.545496	0	202.872056
Std Dev	14.79891307	121.8826976	0.364141718	27.63152204

Optimal Global Paths generated by the three multi-objective algorithms for the standard Map



Inference: The Multi Objective Improved Grey Wolf algorithm proposed can be seen to have lower average in all the objectives as compared to MOGWO and MOEA/D indicating that it works more accurately for the Global Path Planning Problem. The total runtime and standard deviation for MOIGWO is also comparable to MOGWO and is much lower than that of MOEA/D.

Exp 7: 3 simulations using MOIGWO for time varying current:

Due to large computation time for time varying currents, the parameters were changed to obtain a more **realistic** and **practical** path planning simulation.

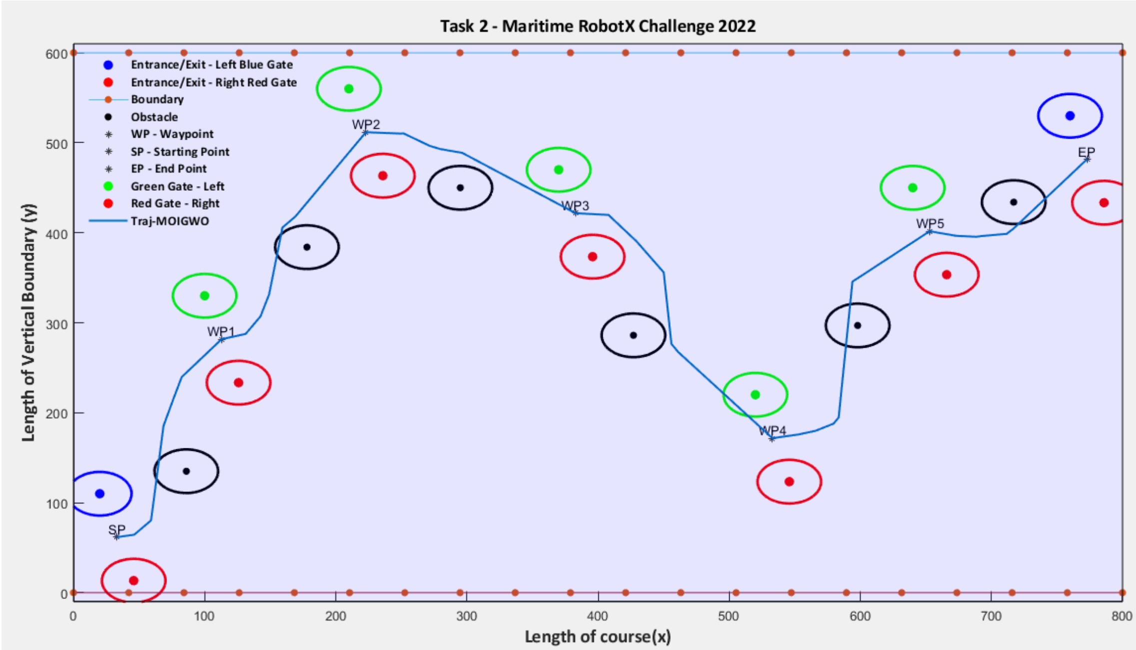
In time varying currents the parameters were set as follows: Bo = 1.2, epsilon = 0.3, omega = 0.4, beta = pi/2, k = 0.84, c = 0.12, Pset = [0.3,0.3,0.4], Lusv = 24.25 dm, alpha = 0.1 (Grid inflation parameter), nGrid = 10 (number of grids per dimension), beta =4 (Leader selection Pressure Parameter), gamma = 2 (Extra Repository Member to be deleted), USV velocity = 5m/s

No of Grey Wolves = 10, No of time Iterations = 10, Archive Size = 10, nVar = 5

Paths	Obj1	Obj2	Obj3	Total Runtime
Path 1	1466.496599	**612.1764909**	**0**	1533.803247
Path 2	1479.718939	724.4155697	0	**1519.798974**
Path 3	**1451.909479**	626.2474833	0	1648.427001

Time Varying Current	Obj 1	Obj 2	Obj 3	Total Runtime
Average	1466.041672	654.279848	0	1567.343074
Max	1479.718939	724.4155697	0	1648.427001
Min	1451.909479	612.1764909	0	1519.798974
Std Dev	11.35772095	49.92502914	0	57.61933893

Of the 10 Pareto paths generated, the path with the lost Normalised Cost was selected in each simulation. Best Overall Path was **Path 1**.



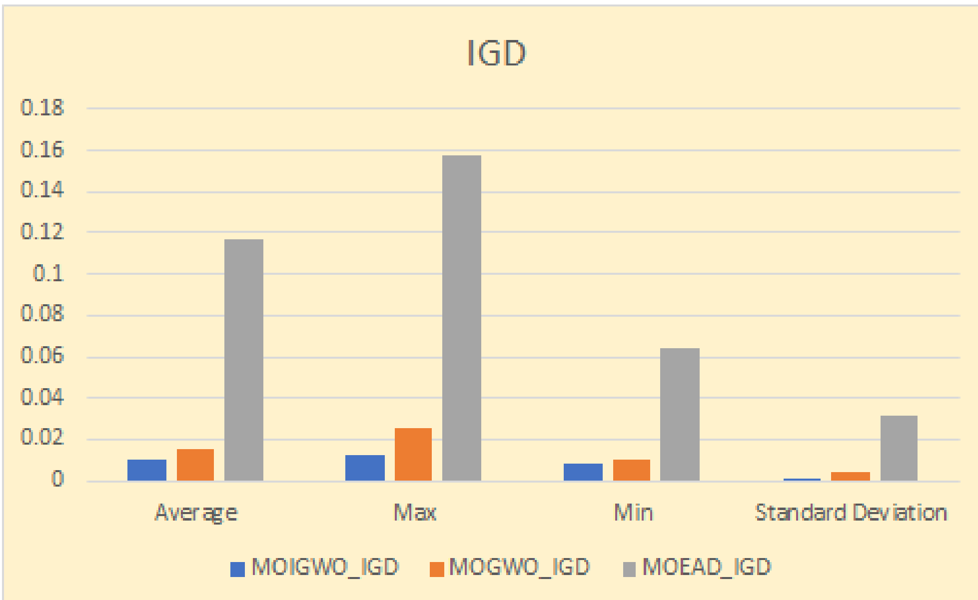
Inference: The Multi Objective Improved Grey Wolf algorithm proposed was found to have an average of 240 secs between each waypoint satisfying all the objectives and constraints in place indicating that it works for the Global Path Planning Problem with time varying current. Due to the large time taken for computation, the Global Path generated can be integrated or provided as the input into the Path Planner when local path planning is implemented. The computation time of Local Path planning reduces substantially.

[59] I acknowledge that the version of MOIGWO has been written using a large portion of the code written by Seyedali Mirjalili, the original author of MOGWO.

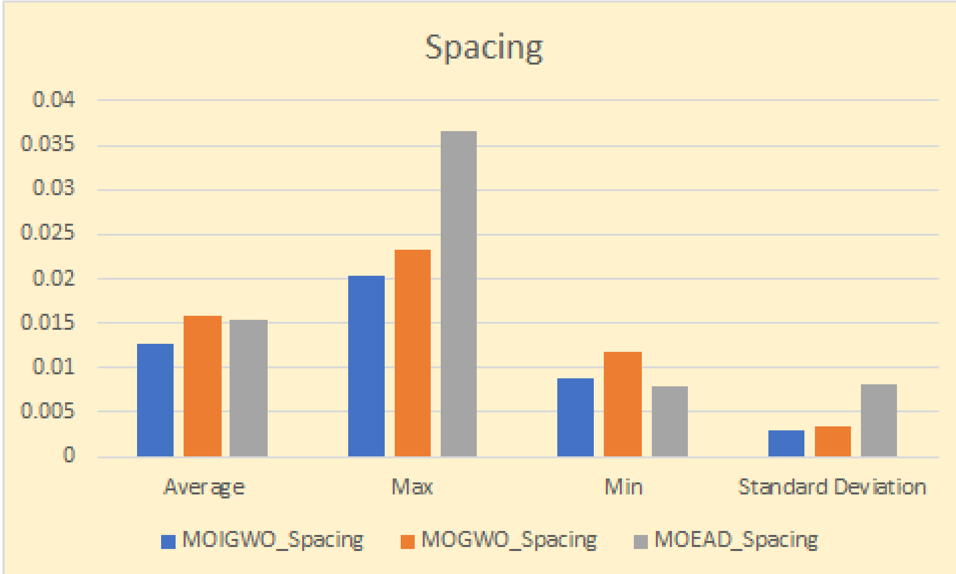
8. Validation: Multi - Objective Optimisation of Zitzler Deb Theile - 3 (ZDT3) Test

[60] The ZDT test suite is one of the widely accepted benchmark functions for the meta-heuristic based optimization algorithm. To prove that the proposed MOIGWO is not only efficient for the specific problem, it can be implemented for a generic problem like ZDT3. The test suite ZDT3 is convex in nature. The prime reason for selecting ZDT3 is because this benchmark function is well defined and employed by several research works, which facilitates the comparison between the new and the existing multiobjective optimization algorithms. In this paper, for the test suite ZDT3, MOIGWO is compared against MOGWO and MOEA/D for a **population size of 100**, **archive size of 100, nVar =3**, **maximum iteration of 500** each for **10 runs**.

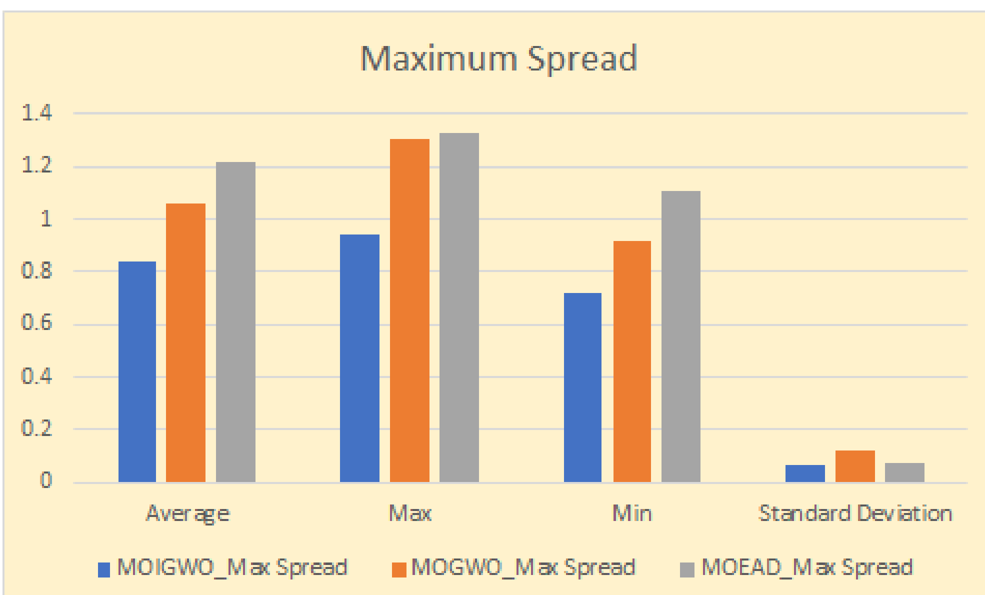
IGD	MOIGWO	MOGWO	MOEA/D
Average	**0.01049983**	0.01566854	0.1172855
Max	**0.012471**	0.025205	0.15783
Min	**0.0080652**	0.0098554	0.064473
Std Dev	**0.00154387**	0.004588061	0.031415374



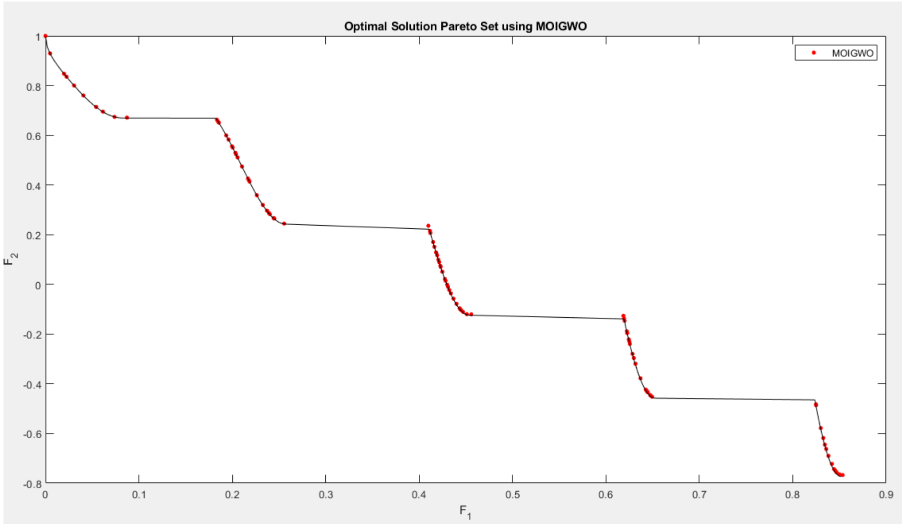
Spacing	MOIGWO	MOGWO	MOEA/D
Average	**0.01274706**	0.0158427	0.01526631
Max	**0.020438**	0.023207	0.036644
Min	**0.0087246**	0.011851	0.0078359
Std Dev	**0.00300282**	0.003489498	0.008222431



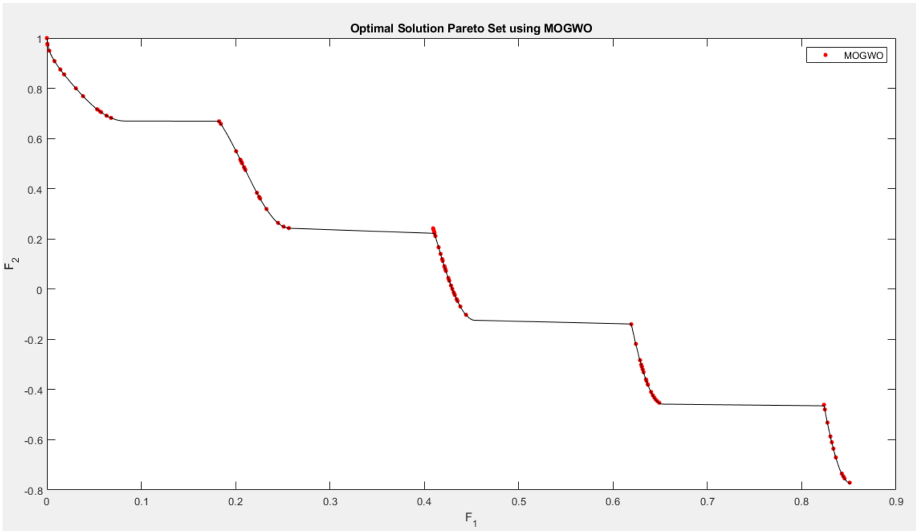
Max Spread	MOIGWO	MOGWO	MOEA/D
Average	**0.842141**	1.063476	1.22023
Max	**0.9407**	1.3013	1.3308
Min	**0.72294**	0.91881	1.1082
Std Dev	**0.065675957**	0.116663435	0.074179472



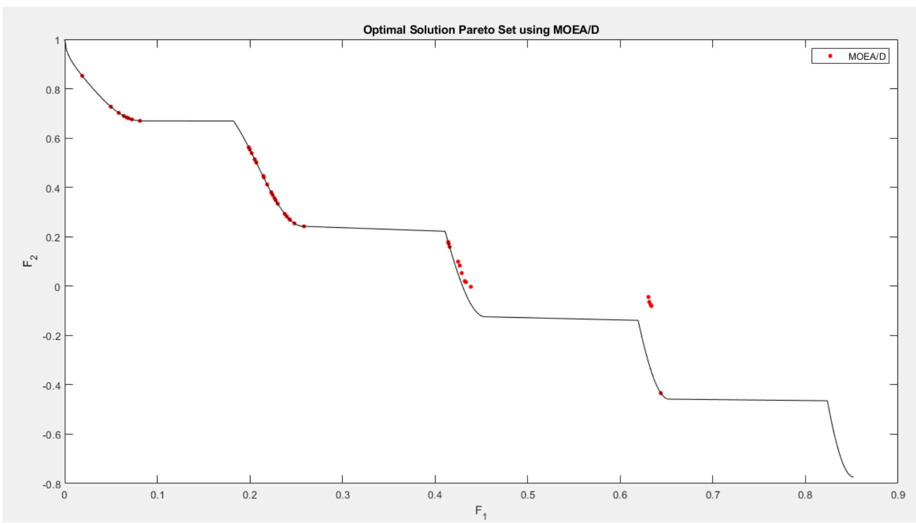
Pareto Front for MOIGWO with Min IGD:



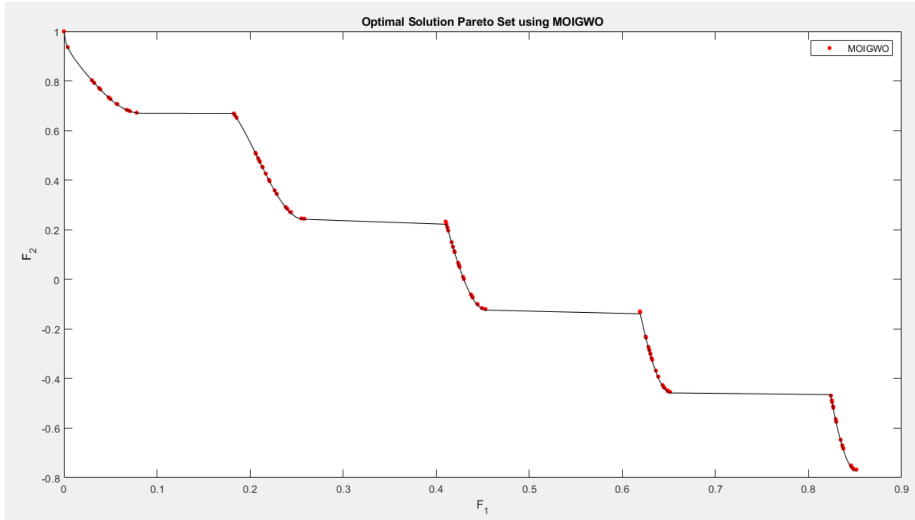
Pareto Front for MOGWO with Min IGD:



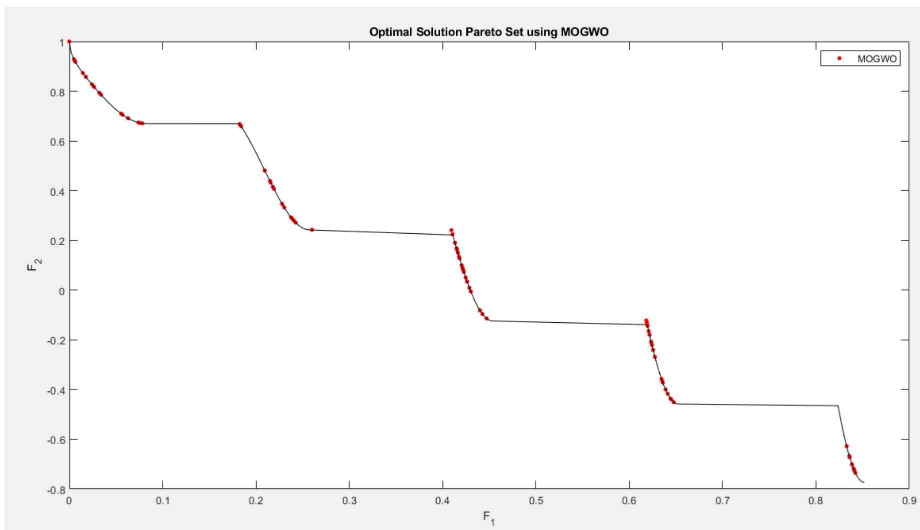
Pareto Front for MOEA/D with Min IGD:



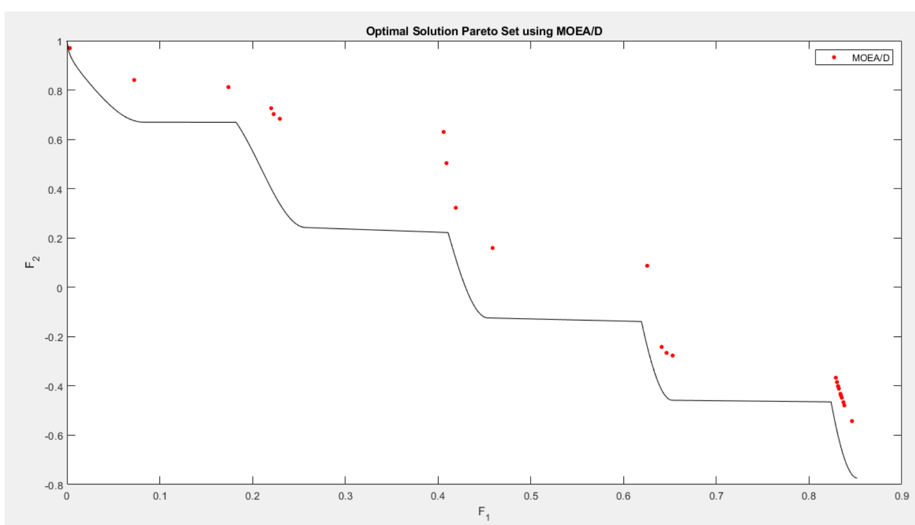
Pareto Front for MOIGWO with Min Spacing:



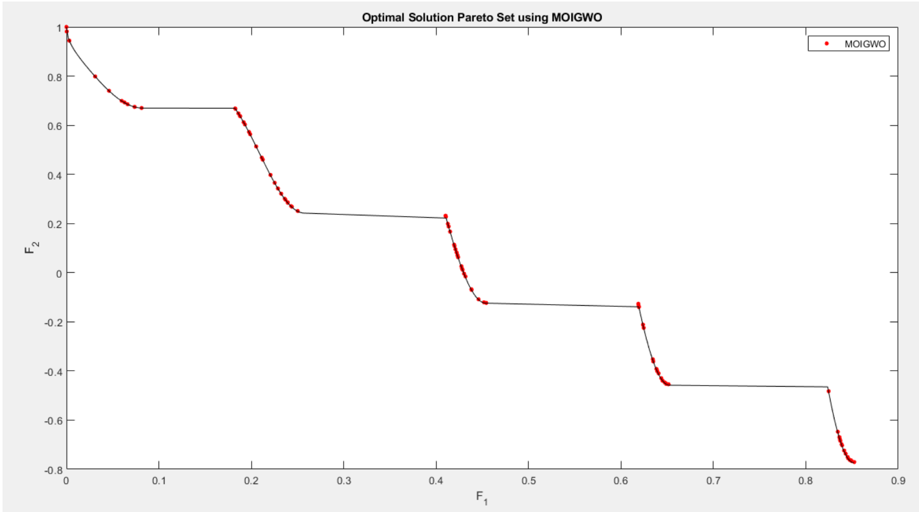
Pareto Front for MOGWO with Min Spacing:



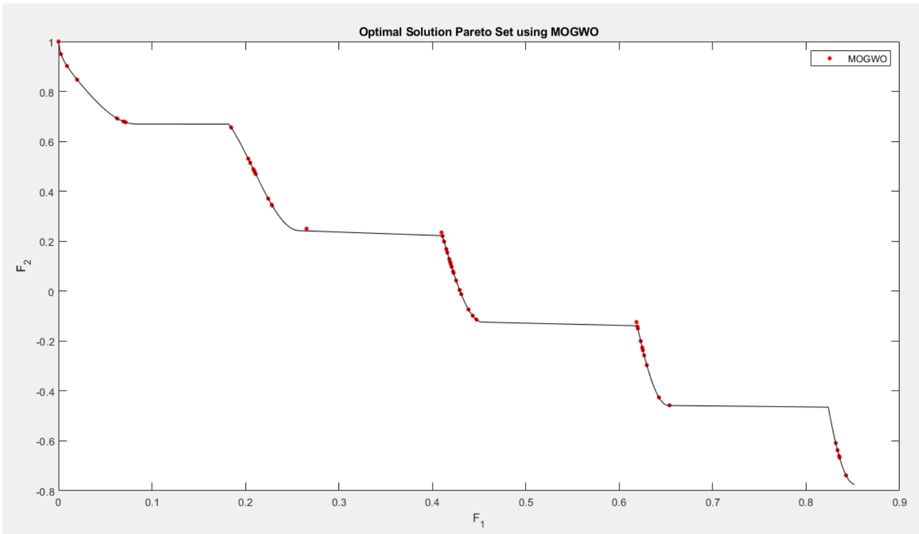
Pareto Front for MOEA/D with Min Spacing:



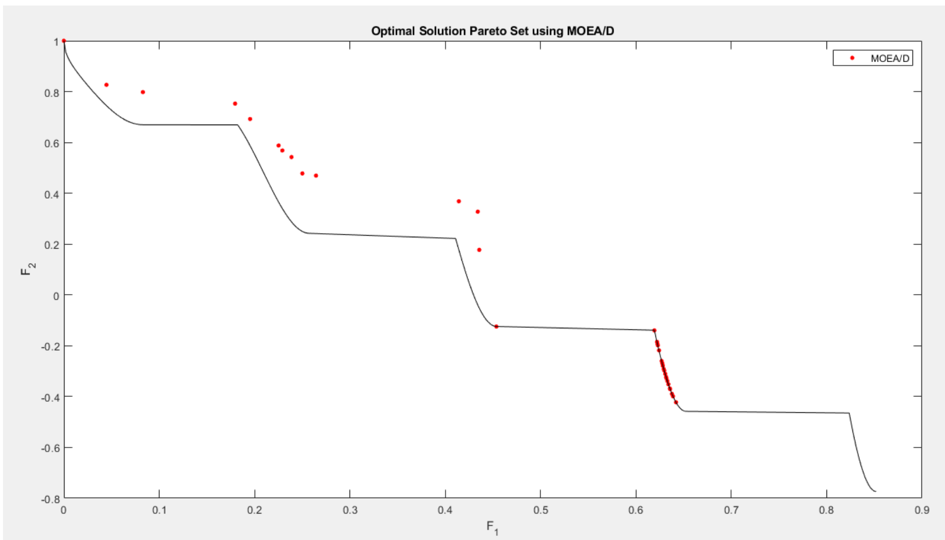
Pareto Front for MOIGWO with Max Spread:



Pareto Front for MOGWO with Max Spread:



Pareto Front for MOEA/D with Max Spread:



Thus, it can be inferred that the Pareto front of MOIGWO is the closest match for the true Pareto front of ZDT3. The average IGD, Spacing and Max Spread is least for MOIGWO and so is the standard deviation indicating higher accuracy of the optimisation algorithm against the benchmark function. Therefore, MOIGWO is even effective in optimizing the multi-objective functions of ZDT3 with the best Pareto front.

The **link** for all the experiment data and related code files can be viewed at:
https://drive.google.com/drive/folders/1hyKimxjqEncyCm9wYc1y28-nliKG_ic3?usp=sharing
(Click EnvFinal_1/2/3.m to run the files to obtain the optimal path and MOIGWO.m/ MOGWO.m/ MOEAD.m to run the validation files)

9. Conclusion:

I. A novel multi-objective Improved Grey Wolf (MOIGWO) has been implemented where a non linearity has been introduced to the factor ‘f’, a chaos factor has been implemented for C and inspired by Particle Swarm algorithm, social harmony and individual learning has been developed for every Grey Wolf particle.

II. The MOIGWO has been successfully implemented for Global path planning. Experiments were conducted to obtain the optimal paths for different numbers of objectives using Pareto Front with the help of an external archive selecting non-dominated solutions. It was found that multiple optimal paths were generated in every simulation with minimum path length, maximum path smoothness and maximum path safety satisfying the Boundary, Angle and Velocity Constraints at every point generated.

III. The MOIGWO’s versatility was tested by generating random maps and it was found that the algorithm managed to find the optimal path in each case.

IV. MOIGWO in comparison with MOGWO and MOEA/D was found to generate 80% more accurate safe paths while having the least Standard Deviation and Average for all the 3 objectives with the least total runtime in most cases.

V. It was found that the average runtime between each set of waypoints was 40 secs for fixed current direction and 240 secs for time varying current.

VI. For easier visualisation and simplification of the Path Planning problem, a 2D environment was modelled using Task2 of the Maritime International RobotX Challenge 2022 as the context.

VII. Validation of the MOIGWO using standard metrics such IGD (Inverted Generational Distance), Minimum Spacing and Maximum Spread against standard multi objective benchmark function ZDT3 and MOIGWO was found to be superior in all the 3 metrics.

10. Future Scope:

I. The improved swarm algorithm can be used for other path Planning problems for mobile robotics and other autonomous vehicles in both static and dynamic environments.

II. The Global Path Planner can be integrated with a Local Path Planning algorithm to test its practicality in real life scenarios. The Global Path generated by MOIGWO can be provided as the input for the Local Path Planner to reduce computation time and data storage.

III. 3D simulation environments such as V-Rep Professional, WeBots, RobotNations's Virtual RobotX Challenge using ROS can be used to test the validity of the path generated by MOIGWO using MATLAB R2020a.

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Timeline:

Project Completed as per Timeline below:

May 2nd - 4th week: Problem Identification, Understanding the complexities of various problems and tasks in Maritime RobotX Challenge, Synthesis of novel solution, Problem Formulation, Assumptions to be taken, Inputs, Outputs and Process of Implementation explored

June 1st - 2nd week: Introducing the dynamics of the environment and its conditions in problem formulation, fine tuning the proposed novel solution to suit the problem, identification of possible configuration space 2D environment for modelling

June 3rd - 4th Week - Modelling of Environment of 2D configuration Space in Matlab R2020a

July 1st - 2nd Week - Implementation of MOIGWO for path planning using MATLAB and visualisation of path on Configuration Space, introducing constraints and objective function

July 3rd Week - Implementation of MOEA/D for path planning for validation of results and experimentation

July 4th - August 1st Week - Validation of MOIGWO against a standard benchmark function ZDT3 using 3 metrics (IGD, Spacing, Maximum Spread) and finalising Report

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