Minimization of Fuel Consumption of a Swarm of Spacecraft through a Genetic Algorithm Approach

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Abstract

As humanity moves closer to forming realistic paths to space exploration beyond that of what we have already accomplished, multiple new challenges have presented themselves. Traditional large spacecraft prove to be unfeasible both logistically and economically for missions where a single problem can completely halt operations, especially in most cases where the probability of complications increases with significance of scientific results a successful mission could provide. Because of this, a swarm of individually autonomous small spacecraft may provide a solution. Due to the decentralized nature of a swarm, any problems faced by one craft do not necessarily affect the others, allowing the swarm to stay operational despite some crafts becoming compromised. Since the logistics problem is already solved by the swarm approach, in this project a way of calculating the optimal trajectory of a swarm of spacecraft minimizing the total fuel consumption is investigated, thus finding both a logistic and economically viable alternative. With an accurate mathematical model of the swarm dynamics, we utilize the metaheuristic method of a genetic algorithm to find optimal parameters. From this approach, we were able to cut the total fuel consumption in half while retaining desirable characteristics of the trajectory such as collision avoidance and final formation constraints.

Background

Despite the stigma that space travel is an incredibly advanced and technical area for humankind, this exact problem was already solved by nature millions of years before humans ever existed. A swarm of autonomous agents moving as a single unit can be seen in flocks of birds, schools of fish, and colonies of ants. They react to disturbances as a whole and can continue to survive even if individual members of the swarm are compromised. An interesting area where something like this could be applicable that is more specific than the general space exploration concept is the exploration of the rings of Saturn. What has held us back is the density and unpredictable size (meters to kilometers) of the ice rocks that make up this region. Sending a large spacecraft into an area of space like this is impossible. A swarm that can avoid obstacles and reconfigure itself can be a solution to this problem.

References

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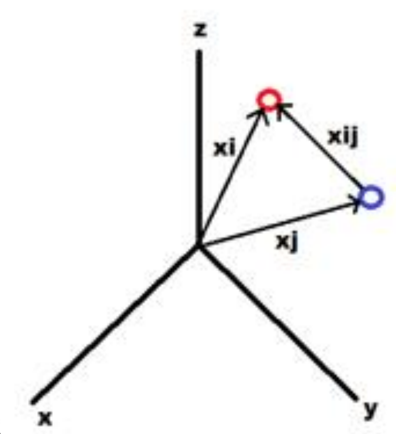
[2] Mallawaarachchi, Vijini, "Introduction to Genetic Algorithms – Including Example Code," *Medium Towards Data Science*, 7 July 2017.

[3] Pesek, Ludek. 1970. *Saturn #26.* The National Geographic Collection

System Dynamics and Algorithm

Mathematical Model of Swarm and Reference System

$$\dot{\mathbf{x}}_i = 2\mu\frac{C_e}{L_e}\hat{\mathbf{x}}_i(|\mathbf{x}_i|-r)e^{-(|\mathbf{x}_i|-r)^2/L_e} - C_h\left[\frac{\mathbf{k}\sigma_n}{\sqrt{\sigma_n^2+1}} + \hat{\mathbf{x}}_n\frac{|\mathbf{x}_n|-r}{\sqrt{(|\mathbf{x}_n|-r)^2+1}}\right] + \sum_{j,j\neq i}\frac{C_r}{L_r}\hat{\mathbf{x}}_{ij}e^{-|\mathbf{x}_{ij}|/L_r} + \sum_m \frac{C_{dm}}{L_{dm}}e^{-|\mathbf{x}_{im}|/L_{dm}} + \mathbf{u_c}$$



Swarm Fuel Usage

$$\sum_i \int_0^{t_f} |m\ddot{\mathbf{x}}_i \cdot \dot{\mathbf{x}}_i|dt$$

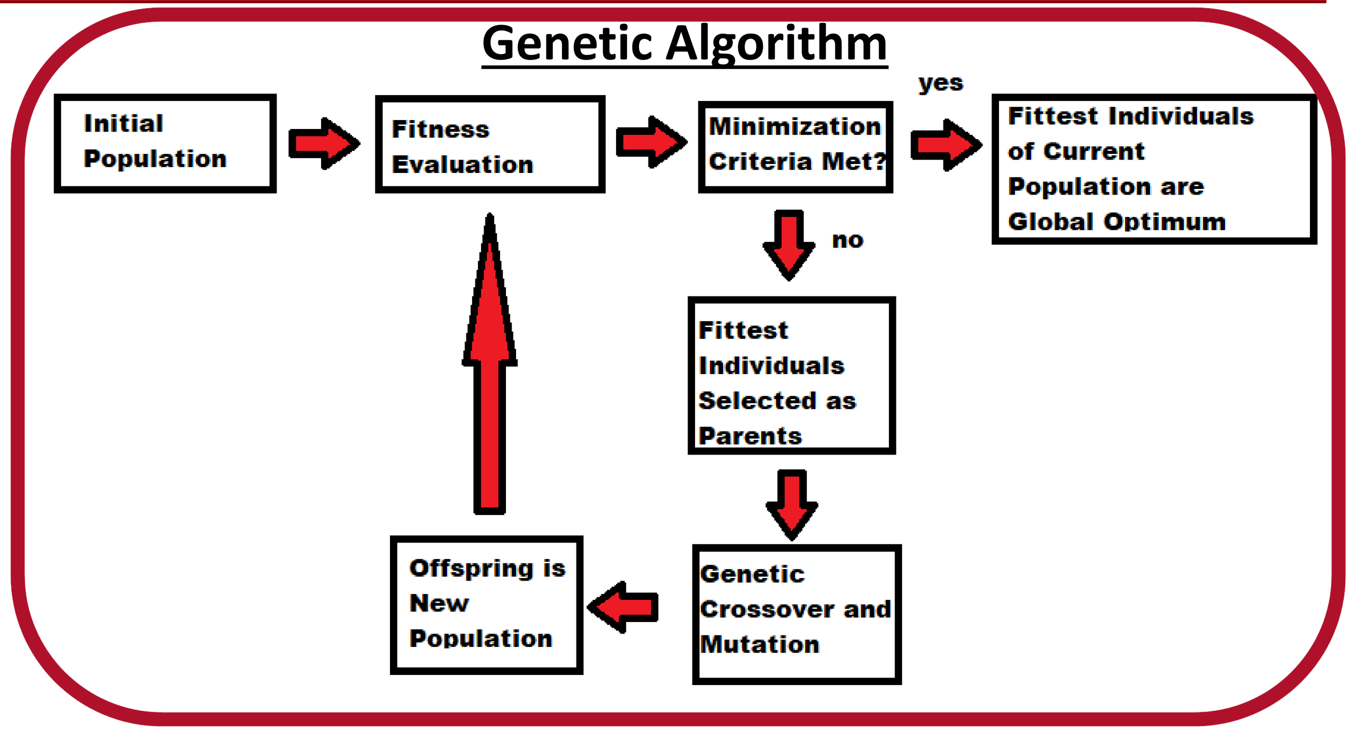
State Variables Parameters

a,b,c	Formation Shape Parameters
C_h	Hyperbolic Potential Magnitude
C_e , L_e	Exponential Potential Magnitude and Length Scale
C_r , L_r	Repulsive Potential Magnitude and Length Scale
C_{dm}, L_{dm}	Craft-Obstacle Repulsive Potential Magnitude and Length Scale
μ	Bifurcation Parameter
r	Swarm Spread Parameter
$\mathbf{x}_i$	Position of i'th Craft

$\mathbf{x}_{ij}$	Relative Position Between i'th and j'th Crafts
$\mathbf{x}_{im}$	Relative Position Between i'th Craft and m'th obstacle
$\mathbf{k}$	Vector Containing parameters *a,b,* and *c*
u_x, $\mathbf{u_c}$	Swarm Velocity in Positive x-direction in Scalar and Vector Form
$\mathbf{x}_n$	$\mathbf{x}_i - \mathbf{u}_c t$ where t is time
σ_n	$\mathbf{k} \bullet \mathbf{x}_n$
t_f	Simulation Stop Time
m	Mass of Craft

A system of twenty vector differential equations derived using the theory of artificial bifurcating potentials is used to model the swarm dynamics. With exponential, hyperbolic, and repulsive potentials, a velocity field is defined in three-dimensions. The magnitude, location, and number of these potentials are manipulated through various parameters in the table shown to the left. A certain set of parameters will yield a specific swarm trajectory with goals of foreign obstacle avoidance, inter-craft collision avoidance, final formation shape, and minimization of fuel consumption. The objective function of this optimization process is the fuel/energy used by the swarm given by the summation of each individual craft's power integral. This is the vector line integral of the force exerted on the craft along its trajectory.

Genetic Algorithm



The genetic algorithm is a method of optimization involving successive simulations where the results of the previous are used to generate the initial conditions for the next in a process that mimics Darwin's theory of evolution. Eventually the algorithm will converge to a global optimum where one generation is not measurably better than the last. In this case, the algorithm was implemented in MATLAB and converged after 71 generations to generate optimal parameters for a trajectory of minimal fuel consumption.

Simulation Results

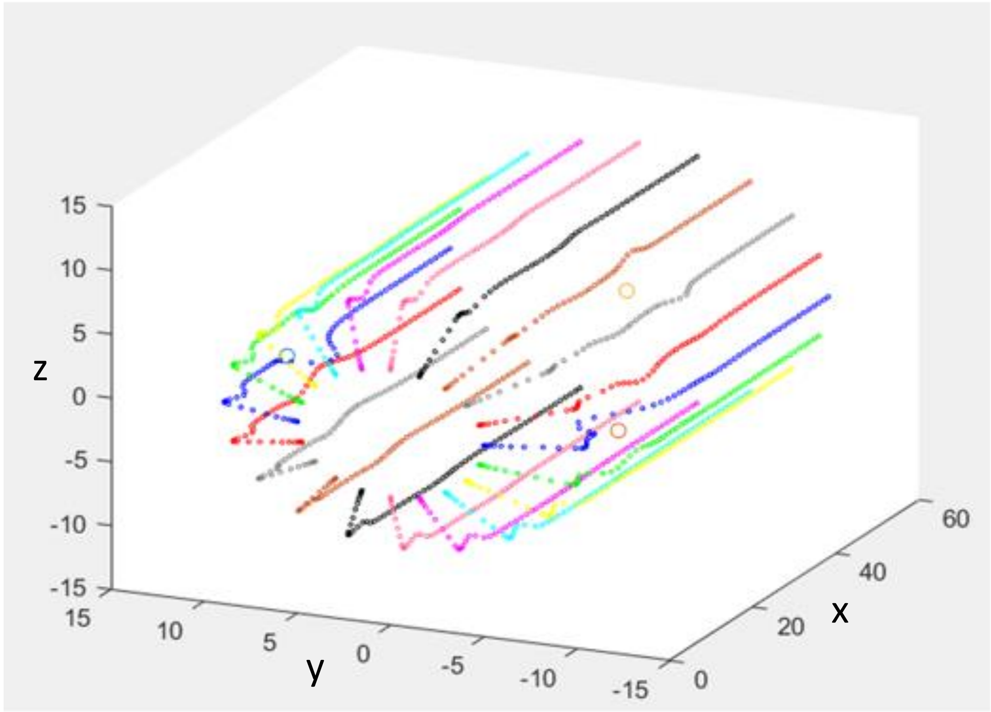


Figure 1: Initial Swarm Trajectory

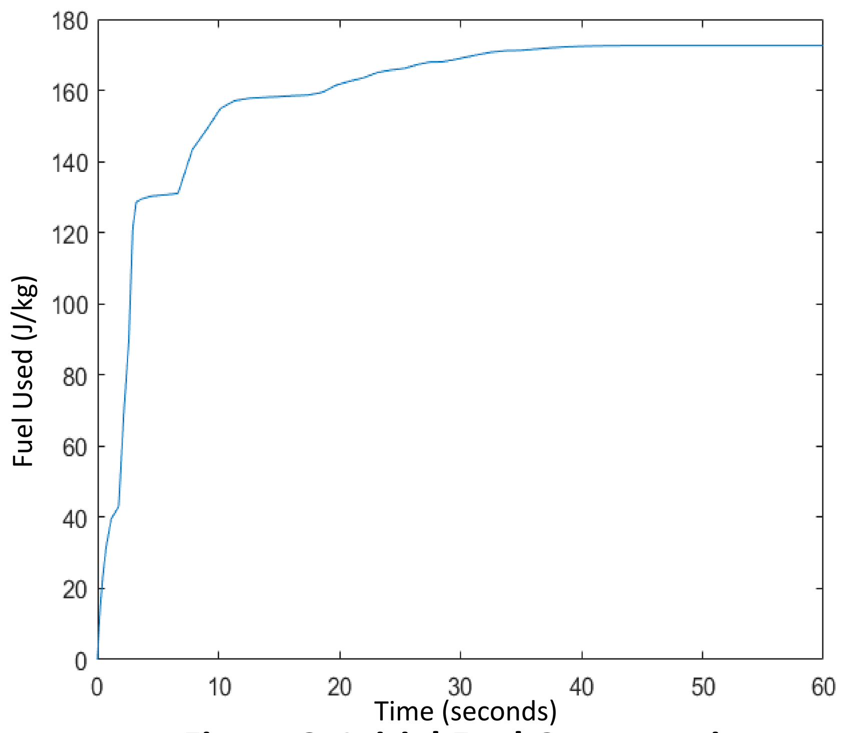


Figure 2: Initial Fuel Consumption

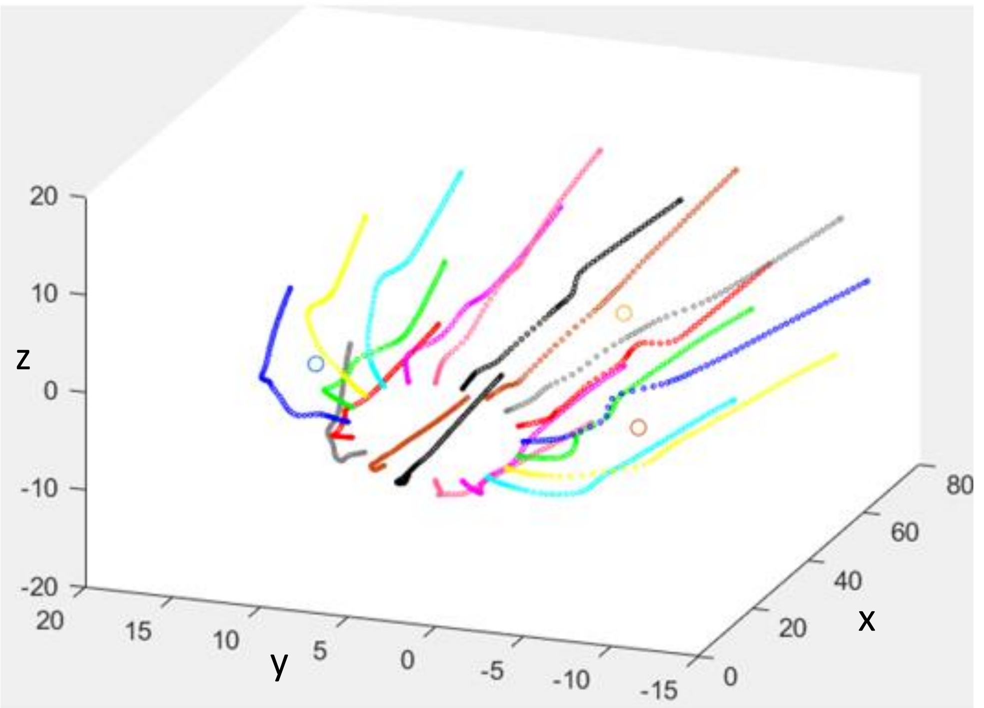


Figure 3: Optimal Swarm Trajectory

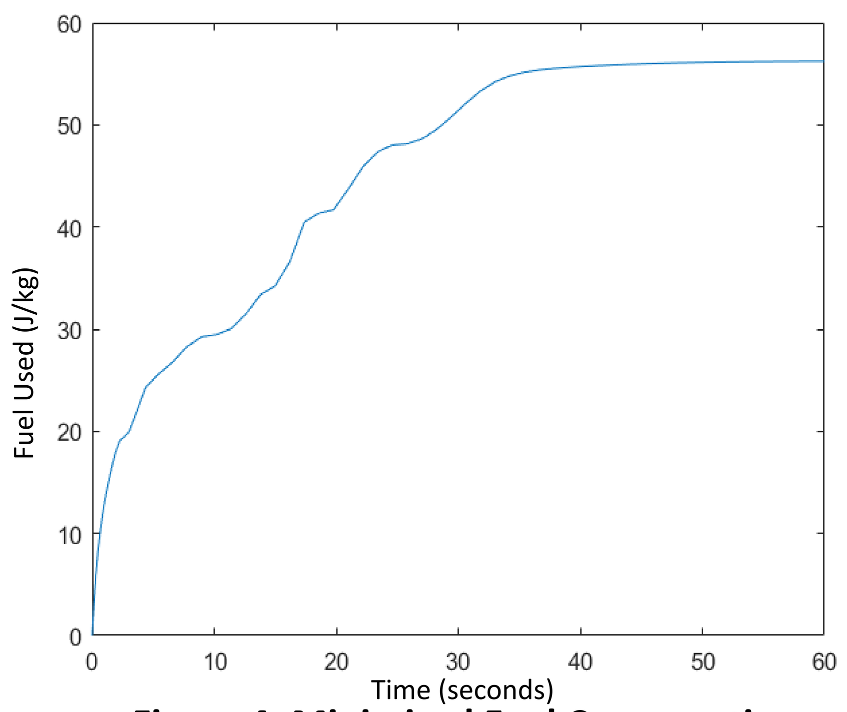


Figure 4: Minimized Fuel Consumption

Each colored group of points represents the trajectory of a single craft for sixty seconds (**Fig. 1** and **Fig. 3**) Larger open circles represent obstacles (ice rocks). In the initial trajectory (**Fig. 1**) sharp spikes in energy/fuel usage occur as a craft attempts to bend around obstacles as well as avoiding others. This is visible in the trajectory of the blue craft as well as the red, gray, and orange crafts above it. The fuel consumed over time (**Fig. 2**) of the blue craft (representative of entire swarm) converges to a steady state value of a little less than 180 J/kg of fuel used. Fuel does not continue to be consumed as the swarm converges to a final formation traveling at a constant velocity in the forward x-direction. After convergence of the genetic algorithm at 71 generations, optimal trajectory parameters are output and used in the dynamical model simulation to create the optimal swarm trajectory (**Fig. 3**). The crafts no longer attempt to sharply swerve around obstacles (**Fig. 3**) and the steady state fuel usage is a little less the 60 J/kg (**Fig. 4**). The rate of fuel consumption is also not as sharp over the course of the trajectory (**Fig. 4**) due to smoother obstacle avoidance maneuvers instead of sudden extreme changes in trajectory. All calculations and visual representations were done/created in the Simulink/MATLAB simulation environment.

Future Direction

For future developments, the MATLAB genetic algorithm code can be cleaned up to run smoother as well as additions to the model that can make it more realistic. Pairing Monte-Carlo simulation techniques along with the genetic algorithm to introduce uncertainty into the system can accomplish this. Comparing this approach to other possible solutions to this optimization problem such as using an MPC or a feedback control loop and using other methods capable of optimizing a function locked as a solution of a system of coupled nonlinear differential equations are all possible avenues to be taken.

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