Ant Colony Optimization for Air Traffic Conflict Resolution

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Introduction

Ant Colony Optimization

Application to Conflict Resolution

Conclusion

Conflict Resolution

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- $\Rightarrow$ Local optimization uneffective

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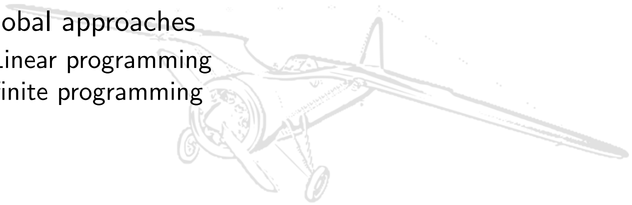

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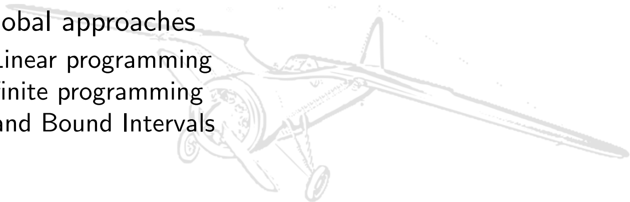

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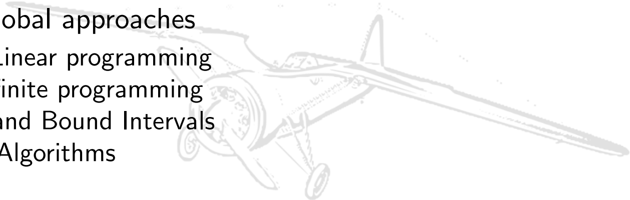

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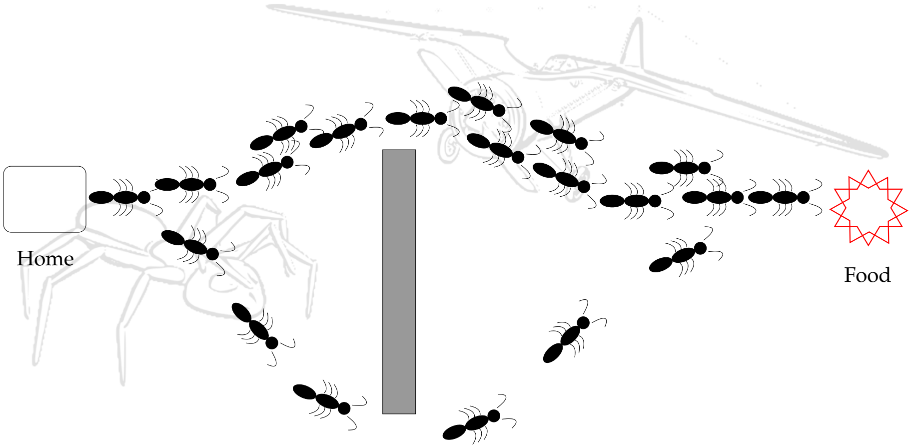
- Iterative approaches : give priorities to aircraft and use local optimization (for example : A^* algorithm).

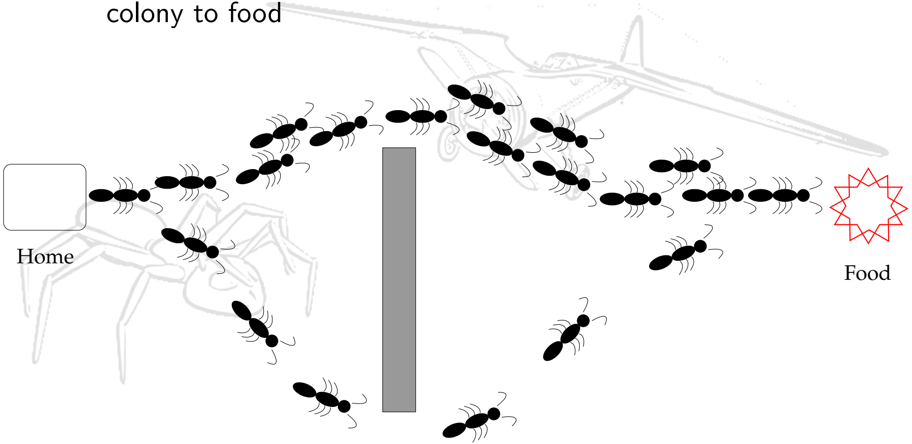
ACO principles

- Use the environment as a medium of communication



ACO principles

- Use the environment as a medium of communication
- Mimic the ants trying to find the shortest path from their colony to food



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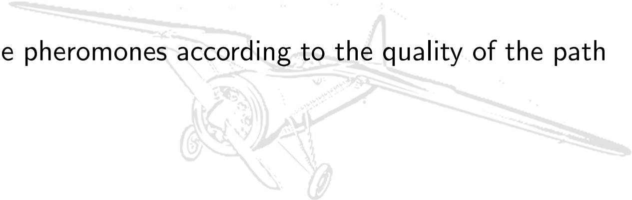

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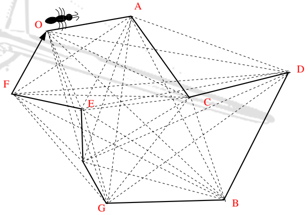
ACO for the Traveling Salesman Problem

- Ants sent on graph. Each ant builds complete path. Choice of next city influenced by pheromone quantity on paths.



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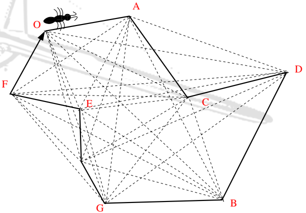

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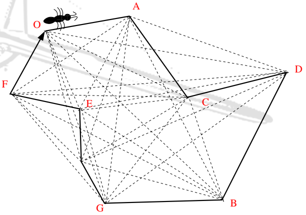

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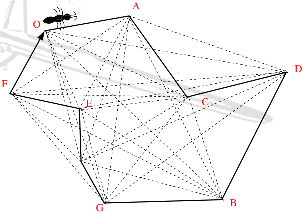
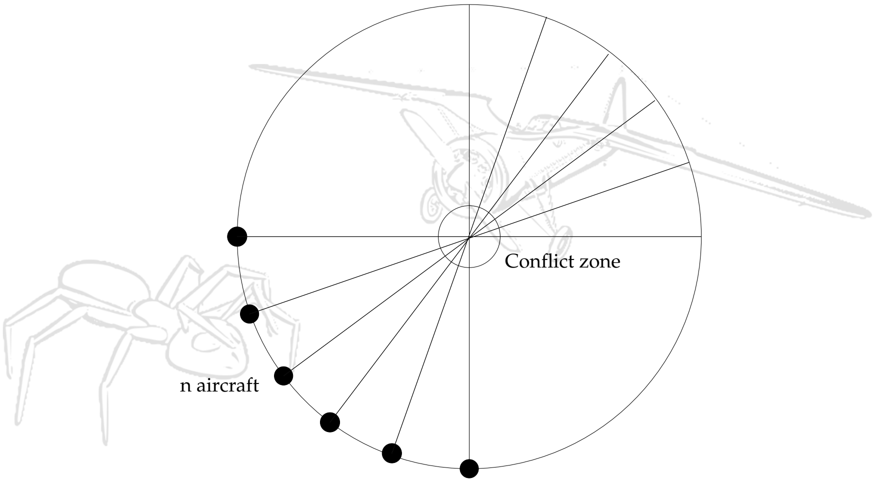
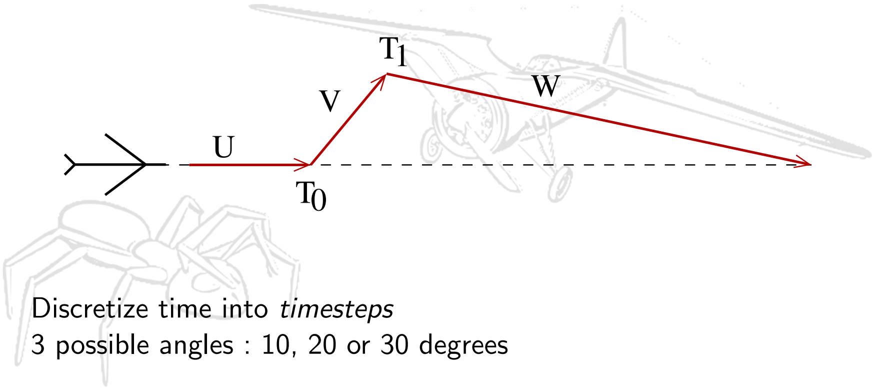


Vidéo

n aircraft conflict example

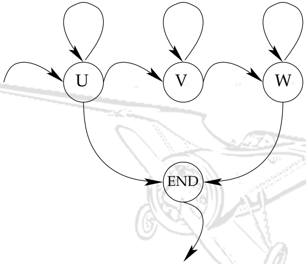


Maneuver modeling



Discretize time into *timesteps*
3 possible angles : 10, 20 or 30 degrees

Possible transitions



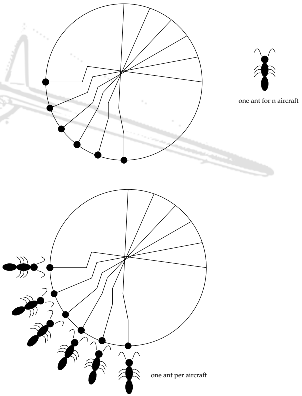
$$U_{i+1} = U_i$$
$$V_{i+1} = V_i + 6$$
$$W_{i+1} = V_i$$

$U_1 = 1,\ V_1 = 6$ and $W_1 = 0$

Number of possible states at timestep $i = U_i + V_i + W_i = 12\,i - 5$

One ant per cluster or one ant per aircraft

- one ant $\longrightarrow$ one cluster



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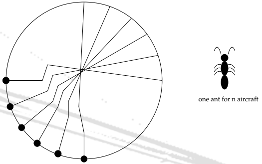

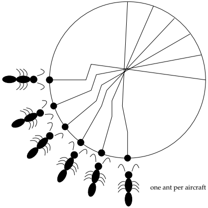

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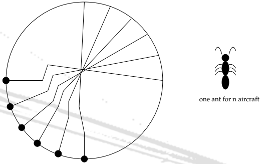

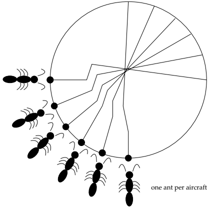

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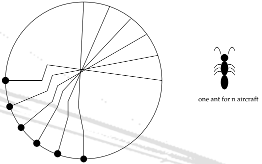

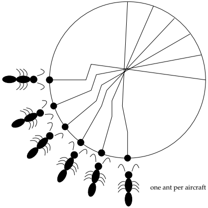

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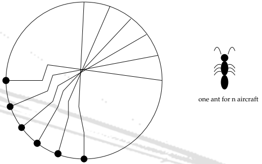

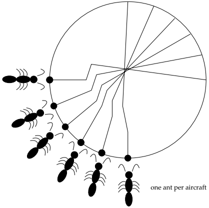

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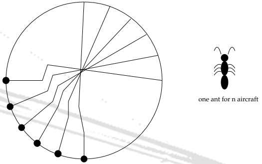
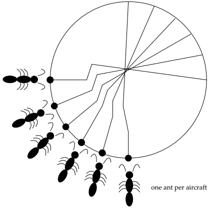
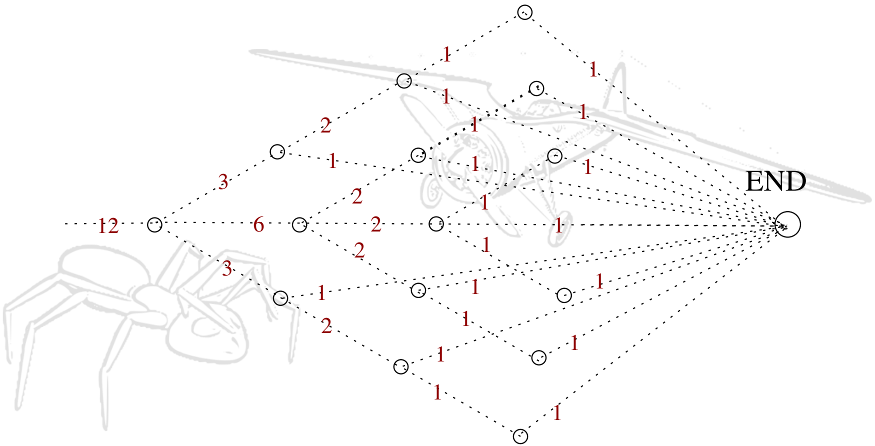
- For $n=30$ and $t=20$: more than 7050 trails instead of 10^{71}





Initial amount of pheromones on the graph



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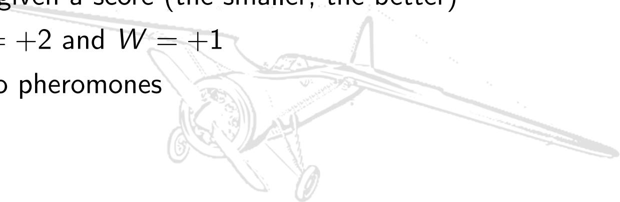

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where n_{out} is the number of ”lost” ants, τ_0 the original quantity of pheromones, and s_{path} the score of the path followed by the ant.

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- At each node, the next edge is chosen with a probability depending on its quantity of pheromones.

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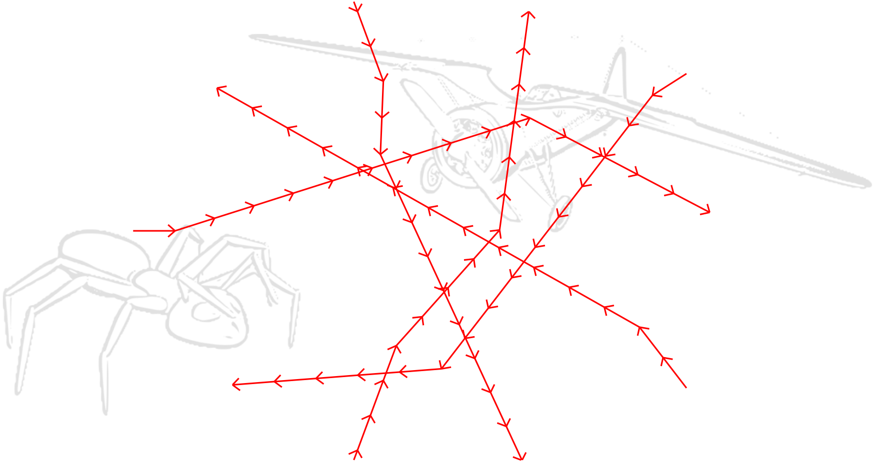
Example of 5 aircraft conflict resolution

18 iterations - score=89



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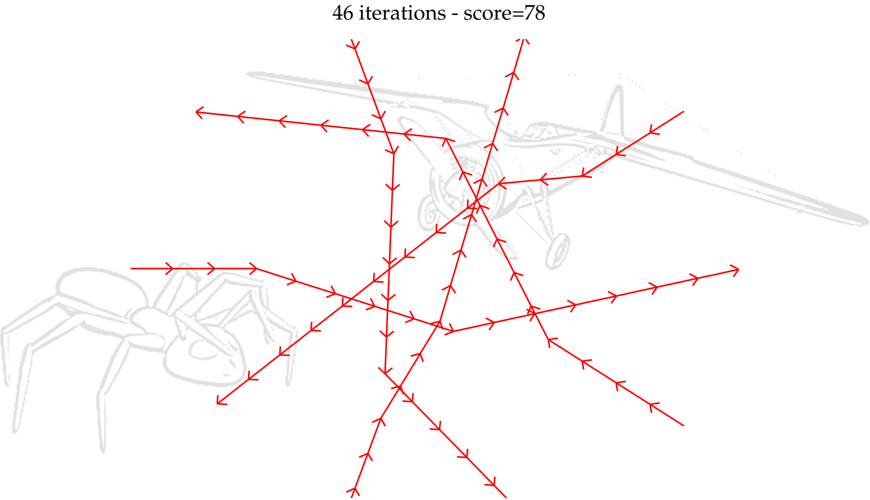

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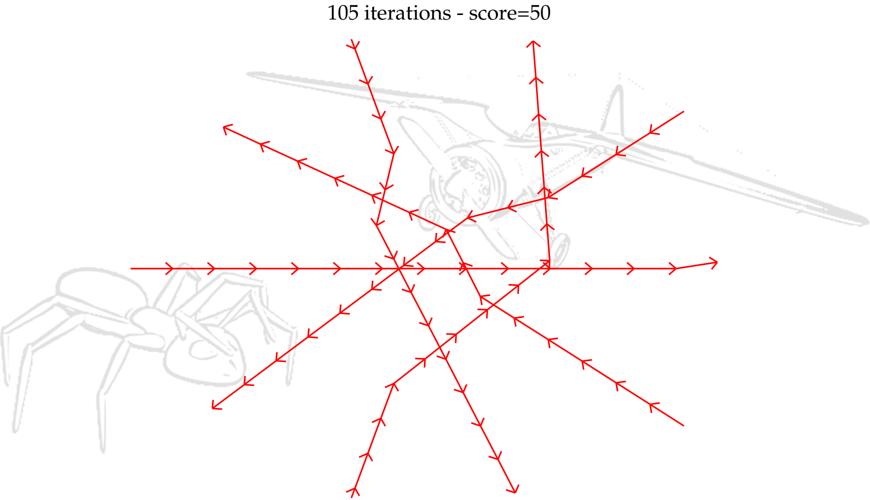

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- Reduce r when the number of ants having less than r conflicts is higher than $\frac{n}{r}$

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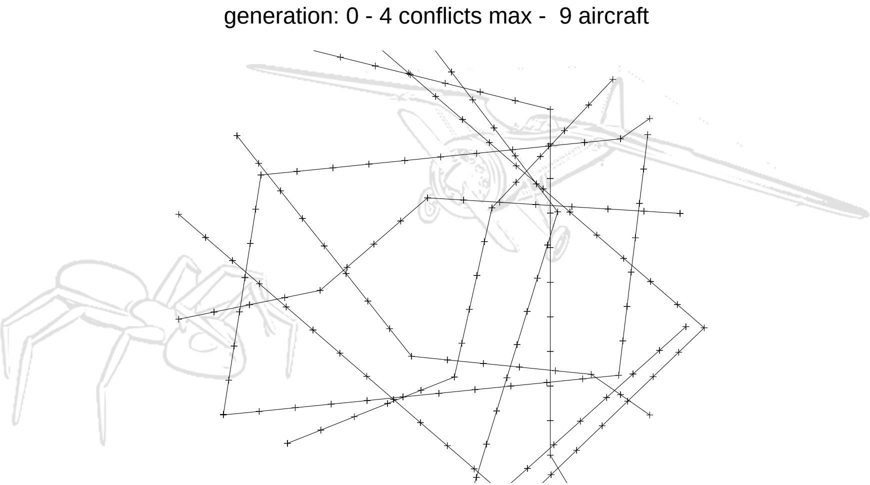

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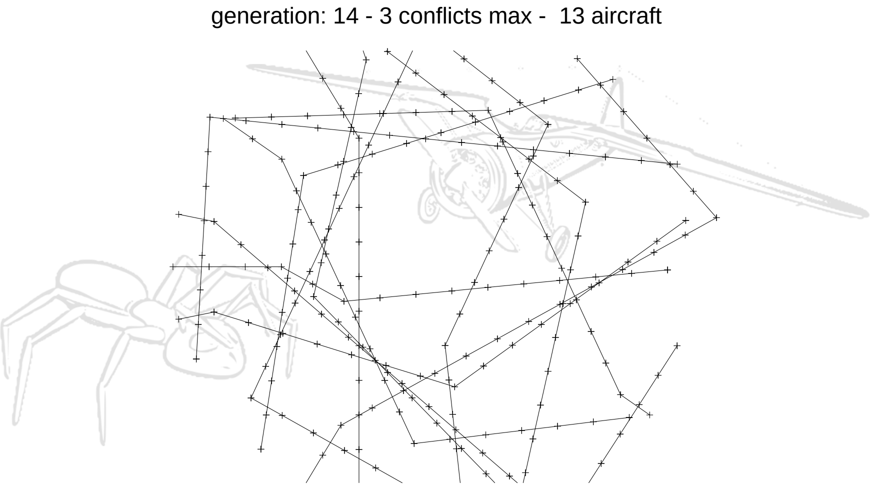

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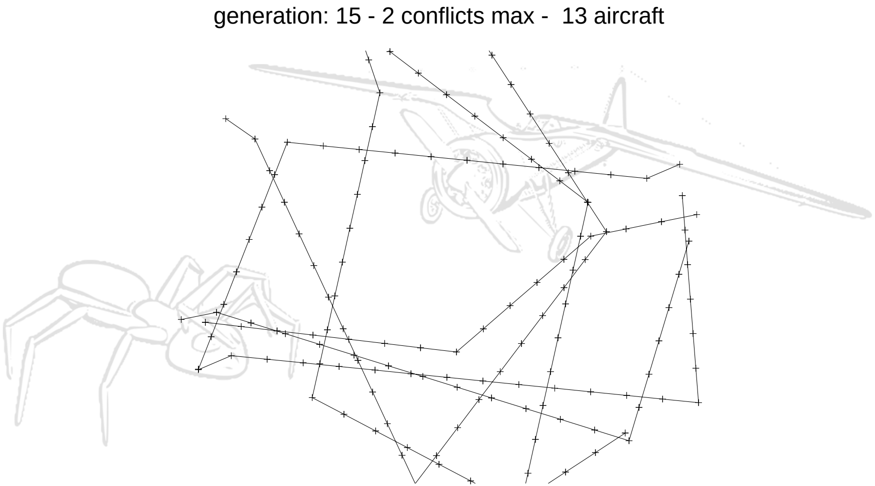

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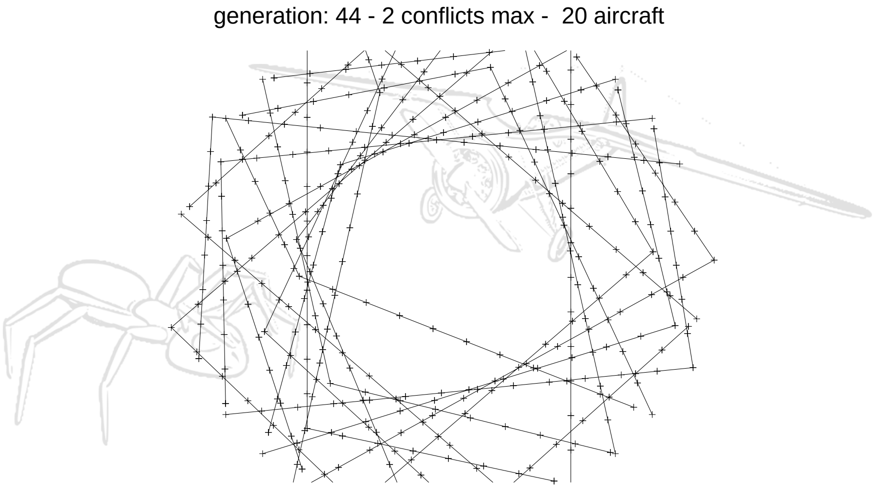

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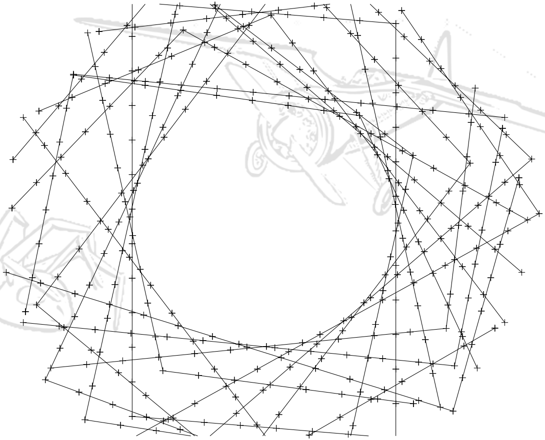
generation: 45 - 1 conflict max - 20 aircraft



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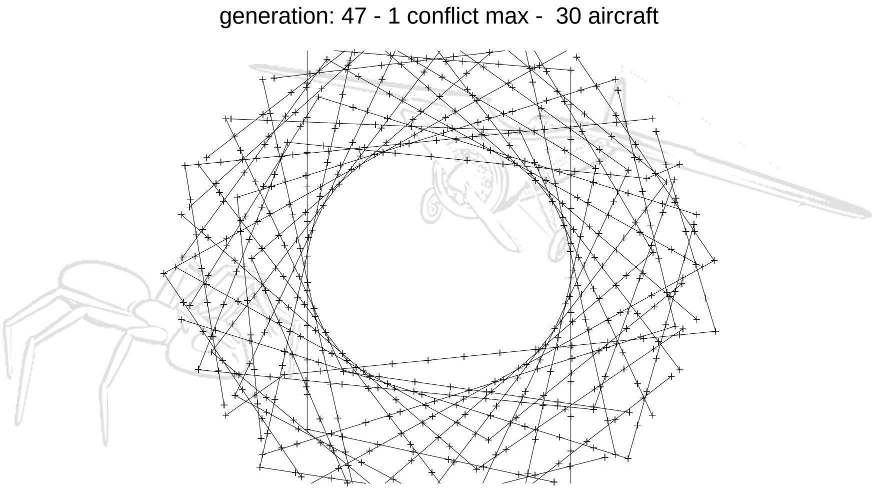

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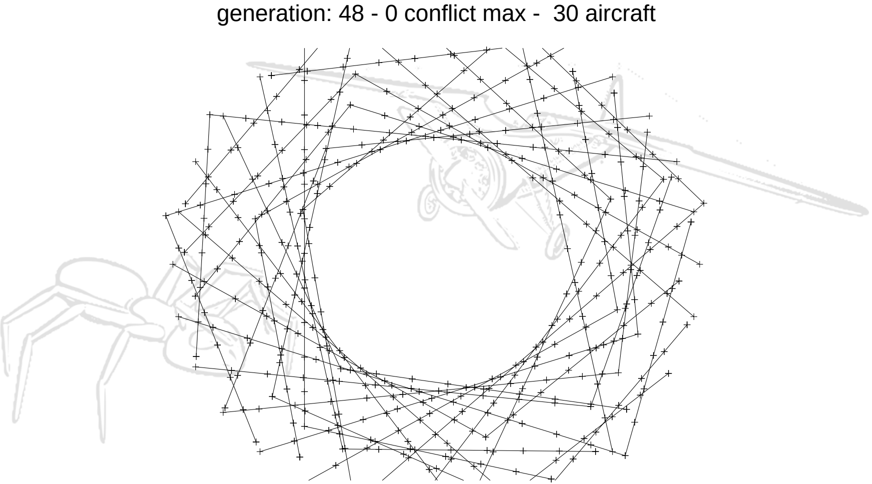

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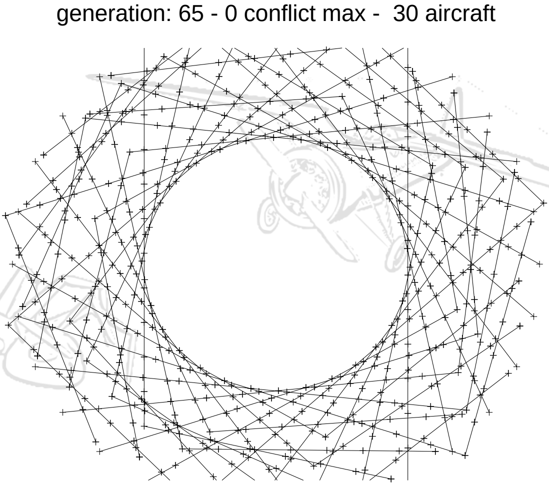

Conclusion

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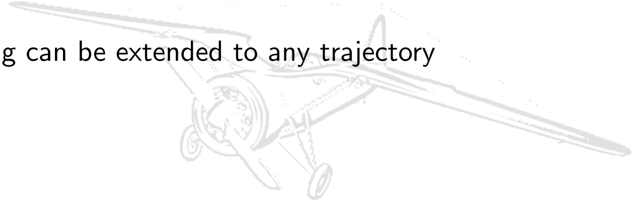

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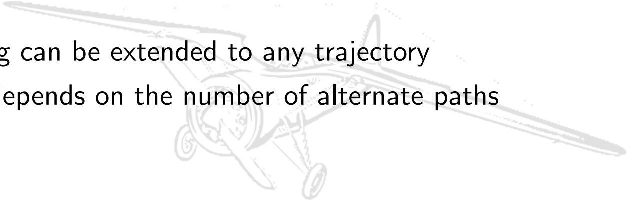

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- Results will be compared to the existing ERCOS (using GAs)
- Stochastic optimization : no guarantee of solution or optimum
- No effective tool offered to controllers without significant enhancement of ground TP