> CollaboTICS

> Master’s Degree in Computer Science

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Degree Program in Systems and Information Engineering

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> Optimization

> What is optimization?

>> Minimize (or maximize) a real function

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> Optimization

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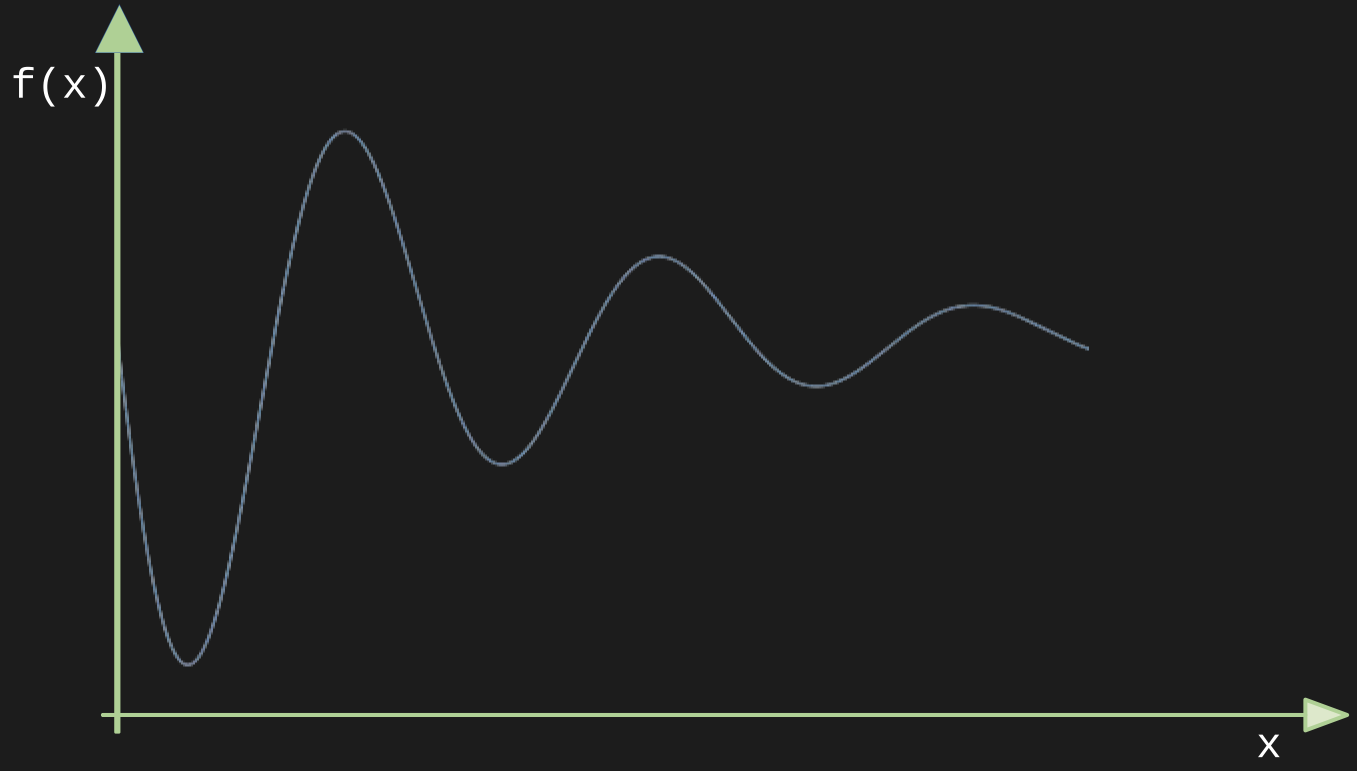

> Optimization

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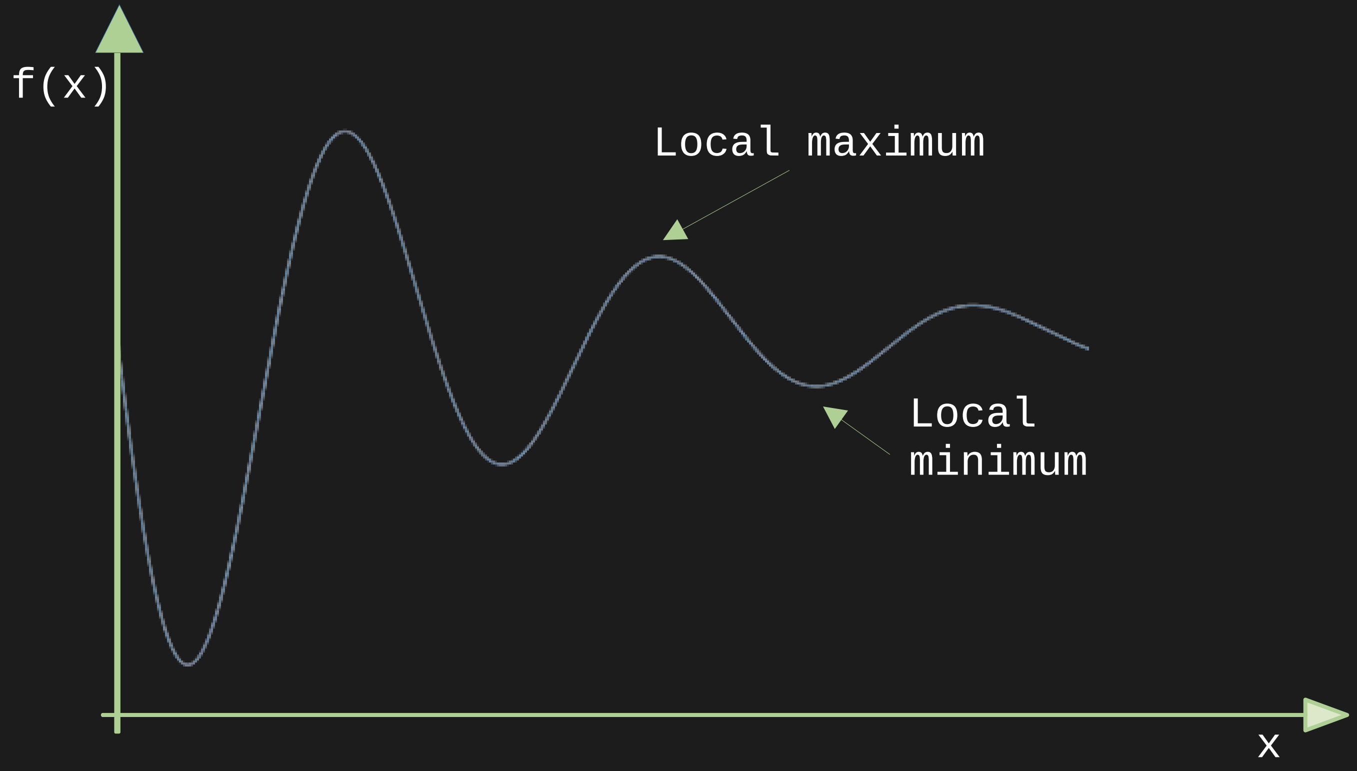

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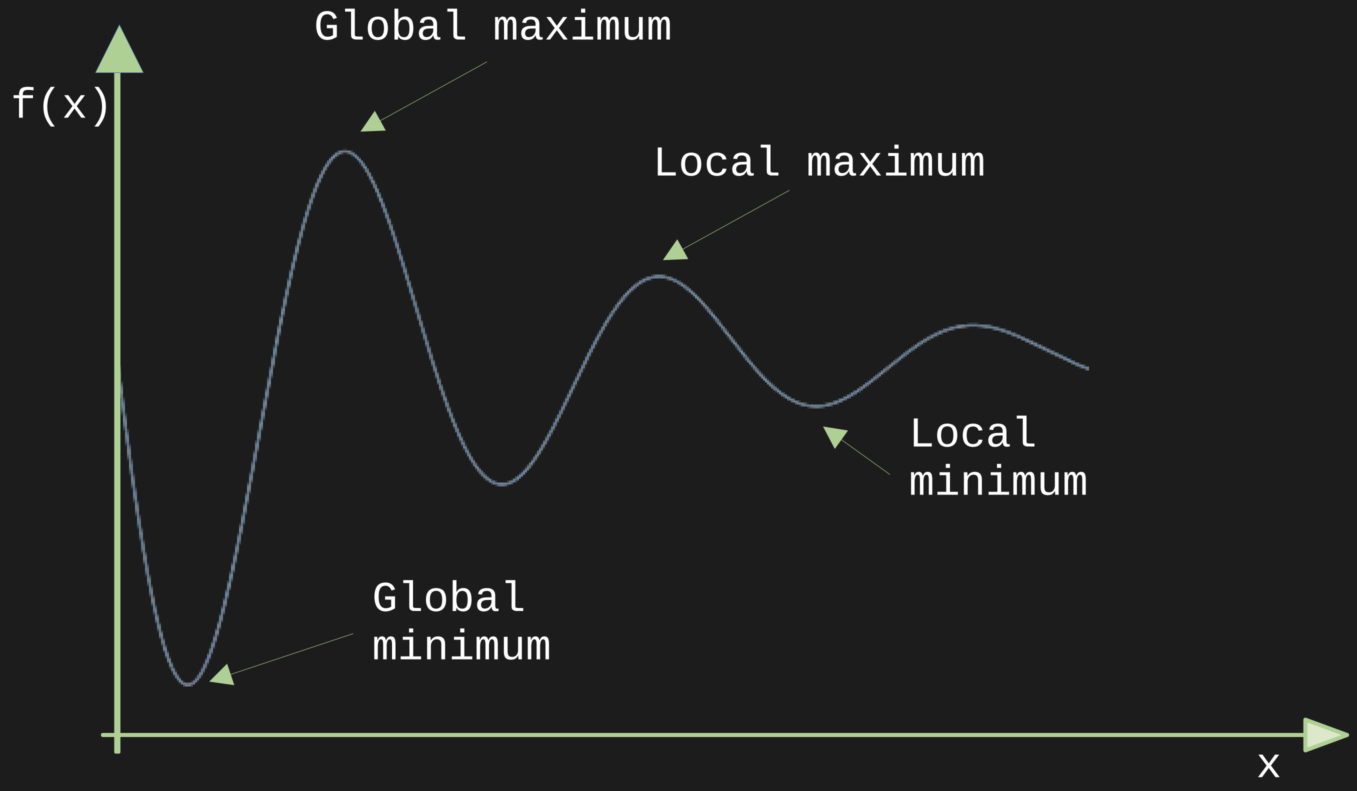

> Optimization

> Different techniques for solving problems

>> Evolutionary computing is part of problem solving techniques

> Optimization

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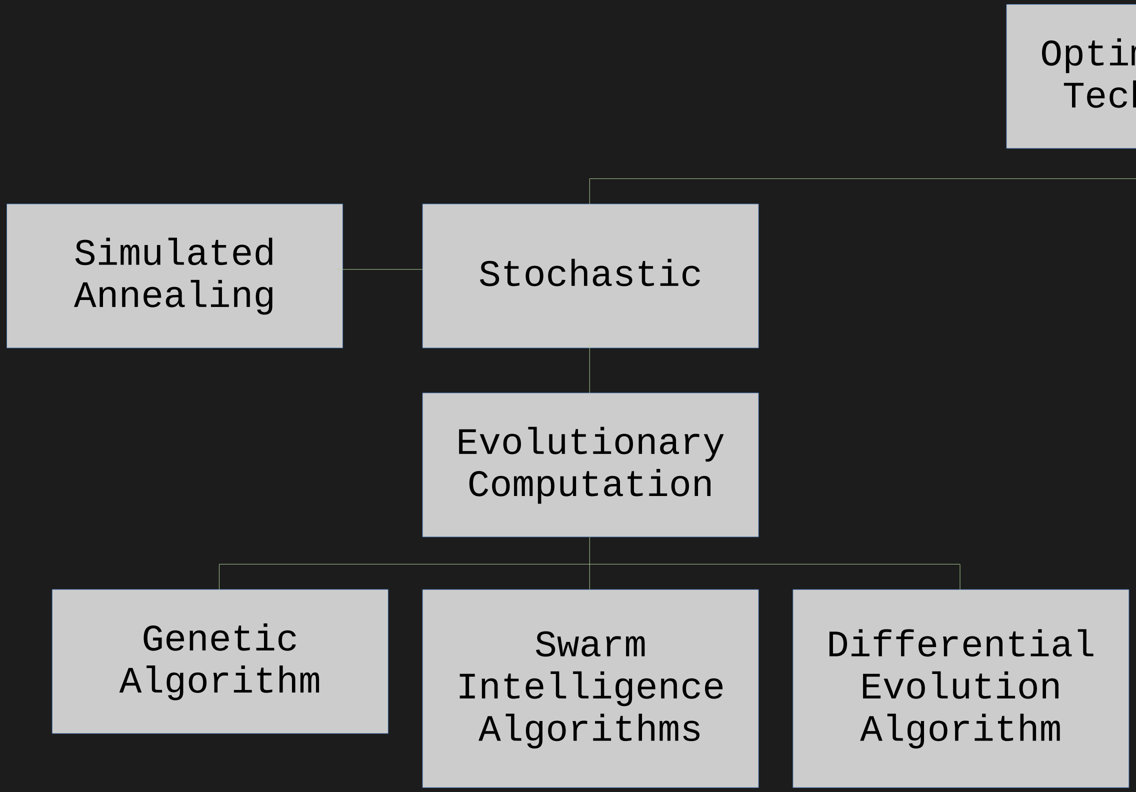

> Optimization

> Different techniques for solving problems

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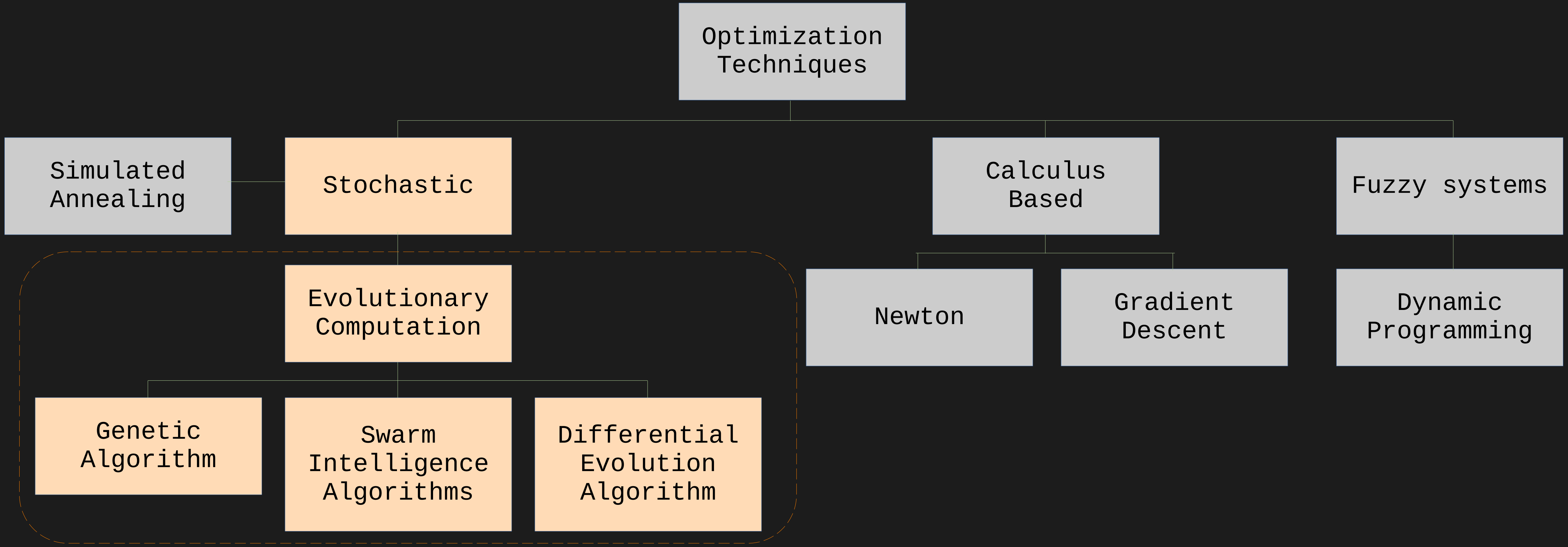

> Optimization

> What are Evolutionary Algorithms (EA)?

>> Evolutionary approaches evolve the set of solutions in order to improve them

>> EAs can be applied to several problems of optimization and in any programming language

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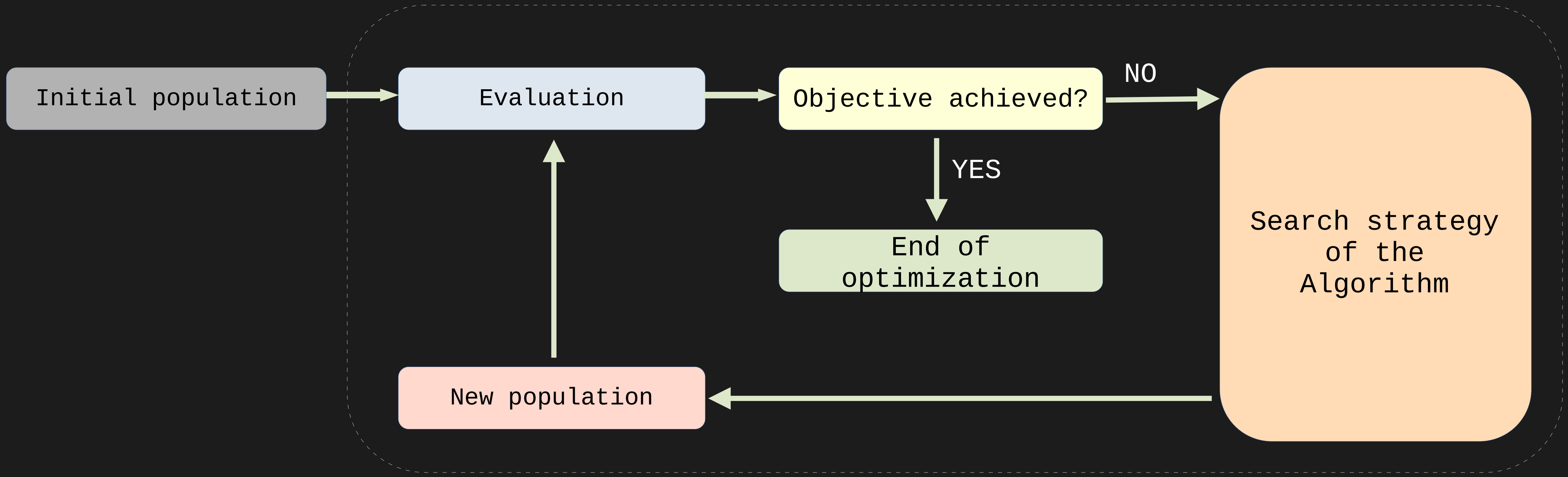
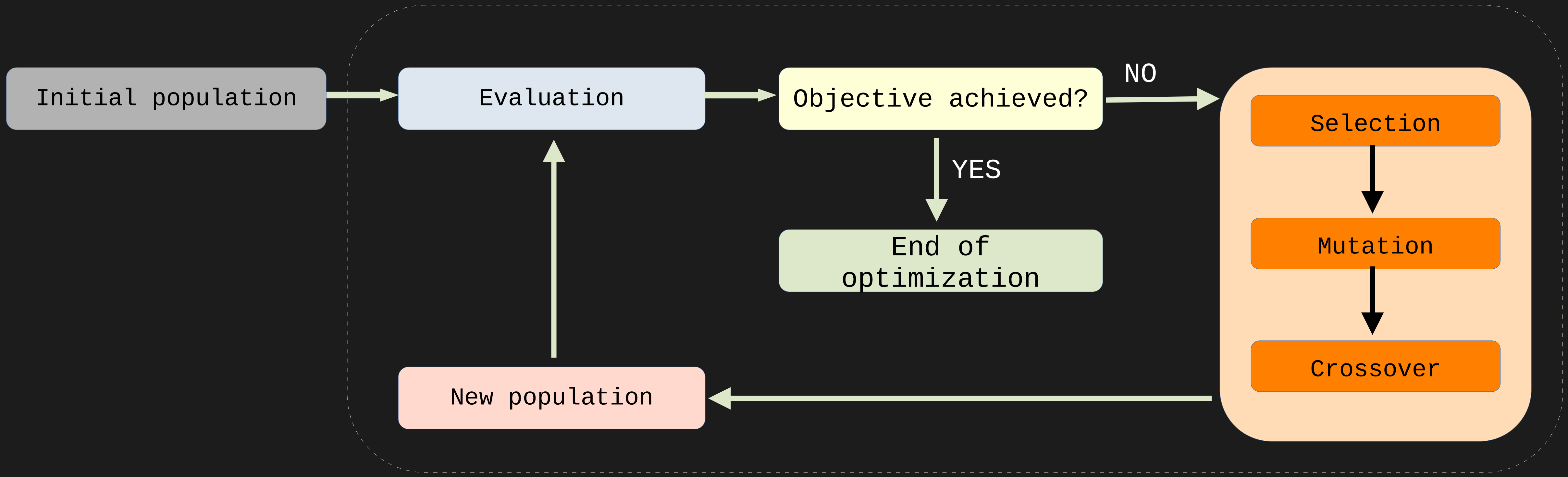


> Optimization

> Genetic Algorithm (GA)

>> Inspired by Darwin’s natural evolution make uses of biological operators such as mutation, crossover and selection



> Example

> Single Objective Problem (SOP)

>> Where it is necessary minimizing the solutions for only one problem

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> Single Objective Problem (SOP)

>> Where it is necessary minimizing the solutions for only one problem

> Steps for solving a problem

1. **List** its requirements, characteristics and constraints
2. **Model** the problem
3. **Choose** one algorithm
4. **Run** the algorithm with the model
5. **Evaluate** the results and analyses the performance

Evolutionary Dynamic Optimization (EDO)

> My research

Evolutionary Dynamic Optimization (EDO)

> Why EDO?

>> **Most real-world problems are Dynamic Problems (DP)**

>> Evolutionary Optimization (EO) have been traditionally focused on the Static Problems (SP)

>> We need to use EDO to cope the Dynamic Problems!

> My research

> Definitions

>> The Dynamic Optimization Problems (DOPs) are characterized by a changing in the fitness *landscape during the optimization* ***and*** *the Algorithm has to react to this change by providing new optimal solutions [2].*

>> The EDO is the set of techniques to solving DOPs using Evolutionary Computation

> Some fields of application

>> Robotics
>> weather forecast
>> Financial market
>> ...
>> Predictive maintenance
>> Control and automation

> My research

> Main differences between SP and DP

> Static Problems (SP)

>> Local and global optimal are fixed

>> Time does not need to be taken into account

>> Once solutions have been found, they will always be valid

> Dynamic Problems (DP)

>> Local and global optimal may change

>> Factors such as time, input data, constraints or domain of the function, can change the problem

>> Once some characteristic of the problem changes, it is not guaranteed that the solutions will remain valid.

> Motivation

> Real-world Problem

> Automatic Train Control (ATC)

>> Objective:
 >>> Minimize the travel time

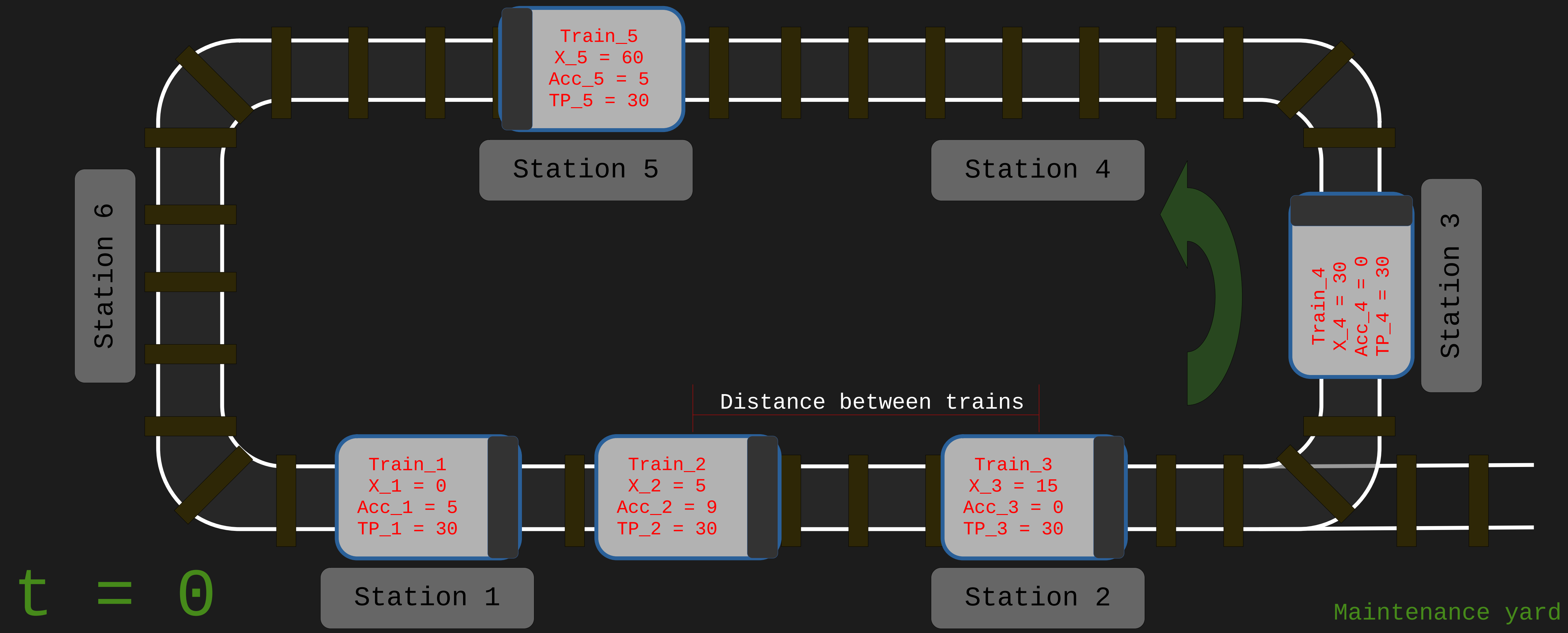
>> Solution:
 >>> Acceleration of each train
 >>> time at platform of each train

>> Static constraints:
 >>> Max acceleration and speed
 >>> Min time at platform
 >>> Min distance between trains

>> Dynamic inputs:
 >>> Number of trains
 >>> Unexpected passenger action
 >>> Operation strategy

> Motivation

> Real-world Problem – Automatic Train Control (ATC)



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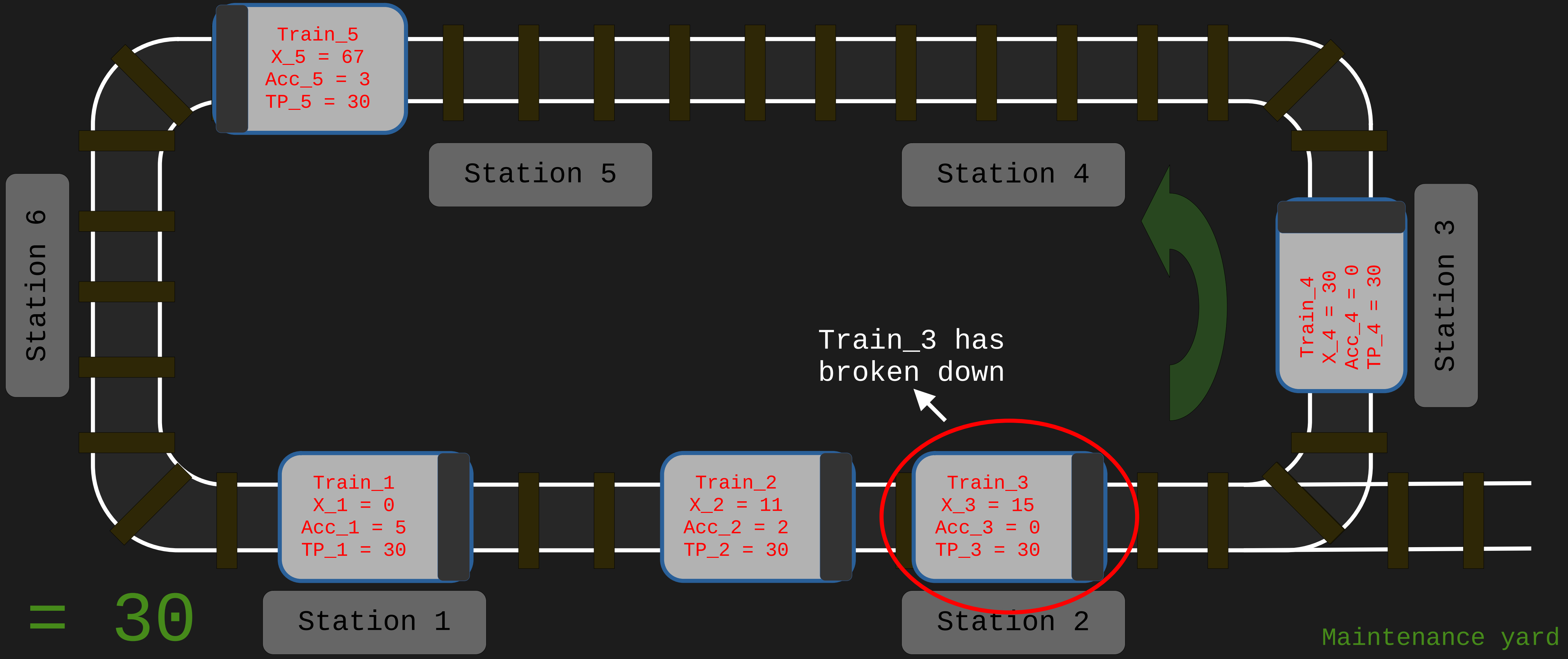

t = 30

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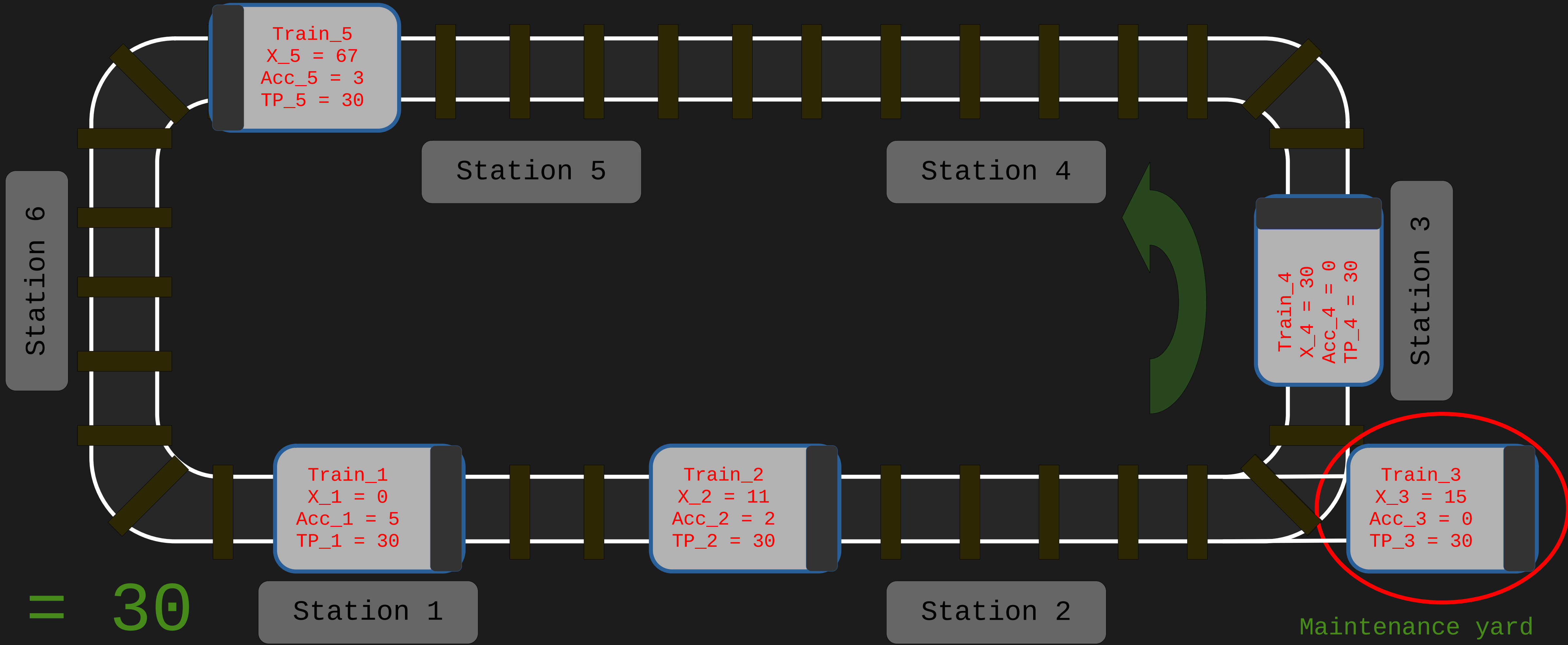

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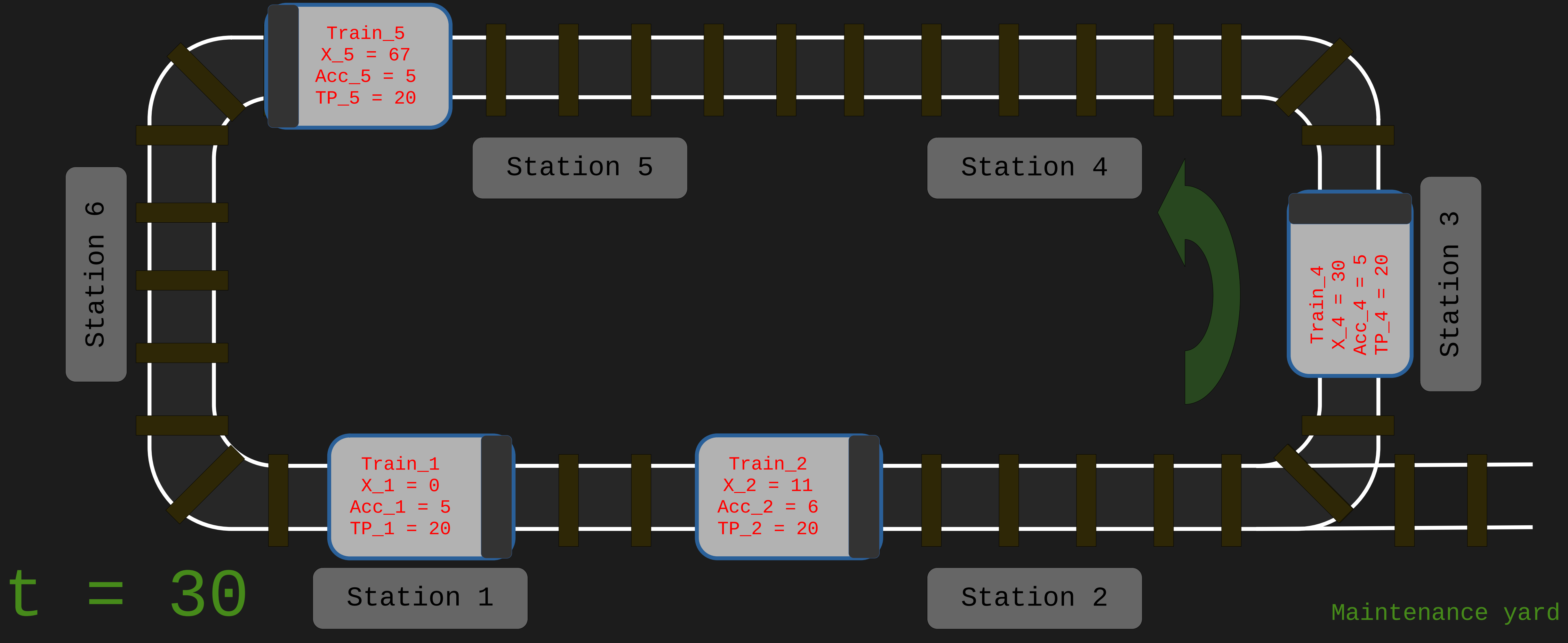

> Algorithms

> Evolutionary Dynamic Algorithms

- >> DE (Differential Evolution)
  - >> DynPopDE
  - >> mbDE
  - >> mjDE
- >> CMA-ES (Covariance-Matrix Evolutionary Strategy)
  - >> mCMA-ES
- >> PSO (Particle Swarm Optimization)
  - >> AmQSO
  - >> CPSO
  - >> FtmPSO
  - >> mQSO
  - >> RPSO
  - >> SPSO
  - >> MPSO

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> Algorithms

> PSO

>> PSO (Particle Swarm Optimization)

>> Population-based optimization technique

>> There is a swarm of particles, and each particle has a position and velocity vector

>> The best particle of the swarm has a influence in others

$$v_{id}(t+1) = v_{id}(t) + c_1 r_1 (Pbest_{id}(t) - x_{id}(t)) + c_2 r_2 (Gbest_d(t) - x_{id}(t))$$

> Algorithms

> MPSO

>> MPSO (Multi-swarm Particle Swarm Optimization)

>> Divide the population into subswarms

>> Apply re-evaluation for change detection

>> Within the sub swarms applies the concept of quantum (probability) particles, increasing the diversity

> Benchmarks

> Benchmark for Dynamic Optimization

>> Moving Peaks Benchmarks (MPB) [10]

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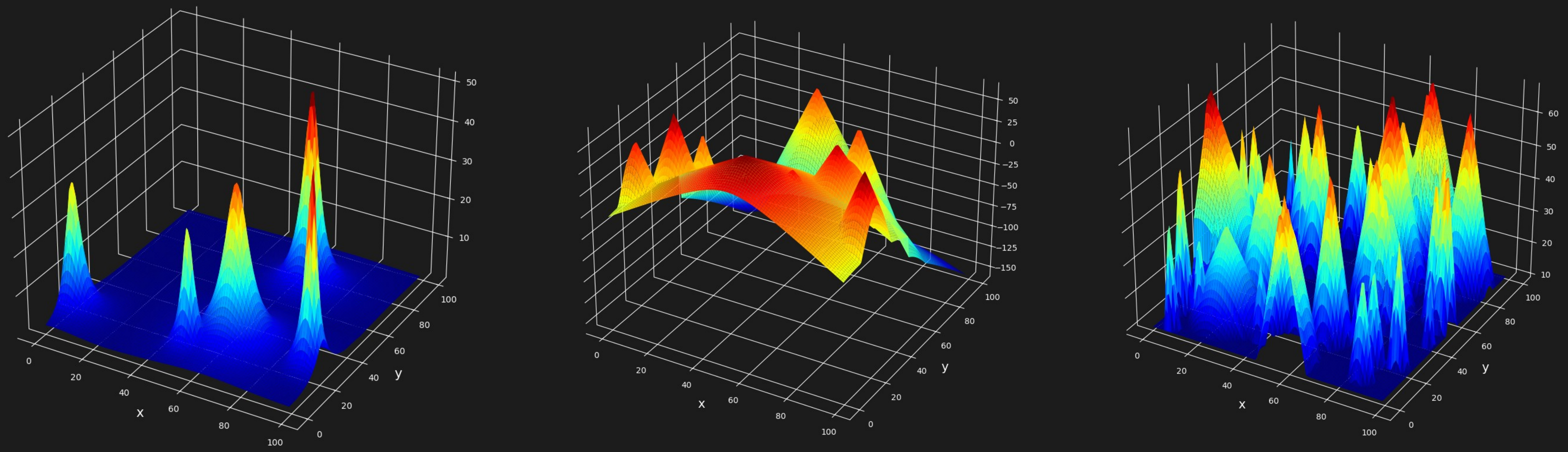
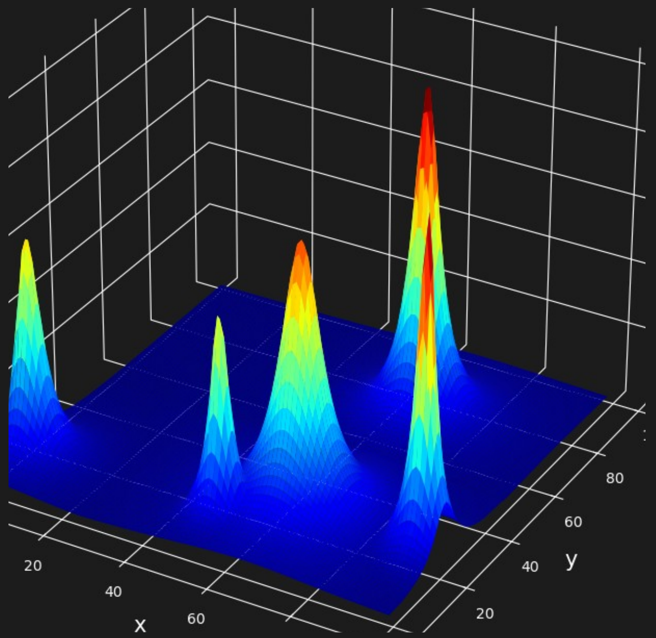
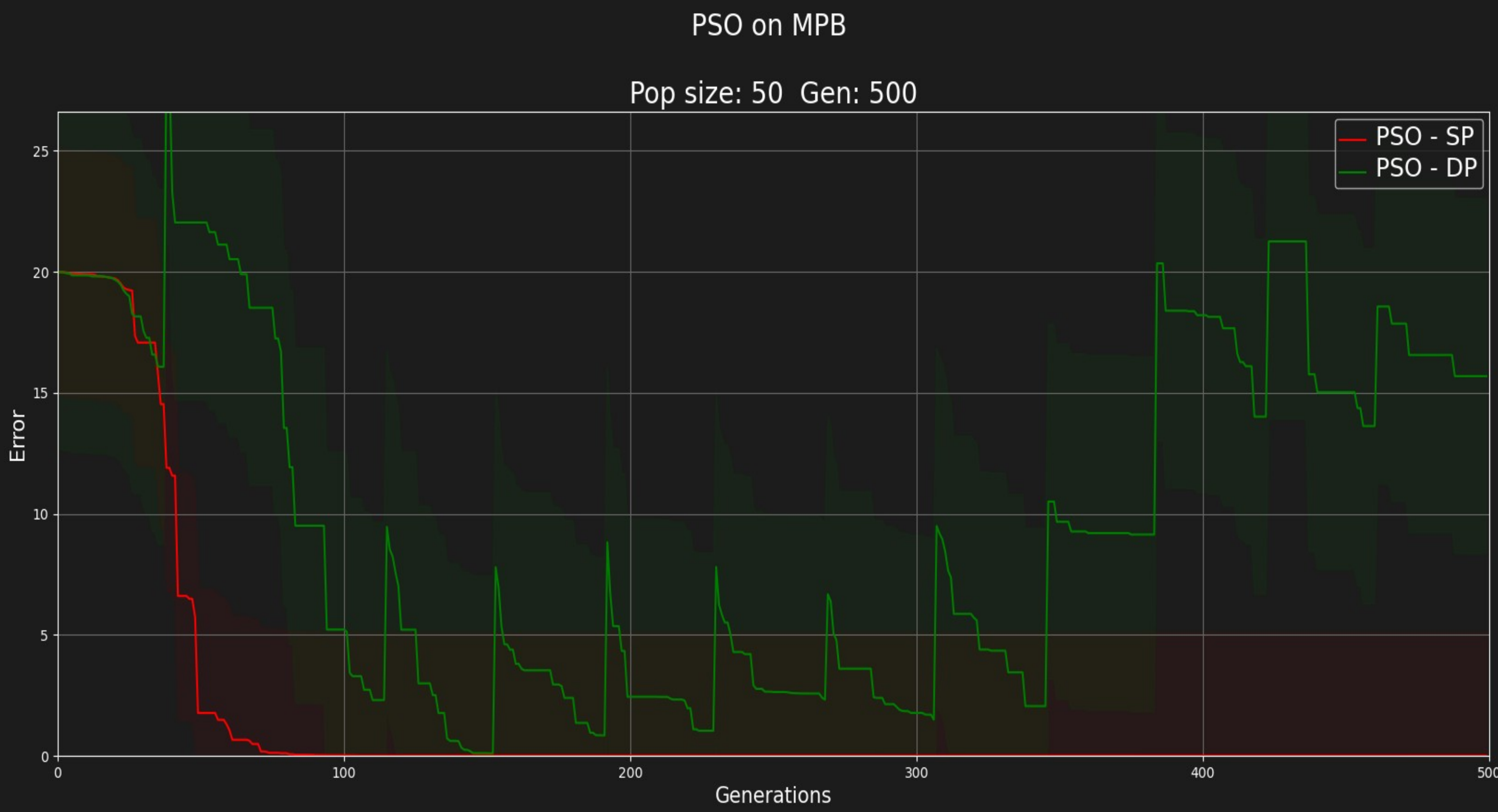


> Analysis

> PSO

>> PSO running in both static and dynamic problem (Moving Peak Benchmark)





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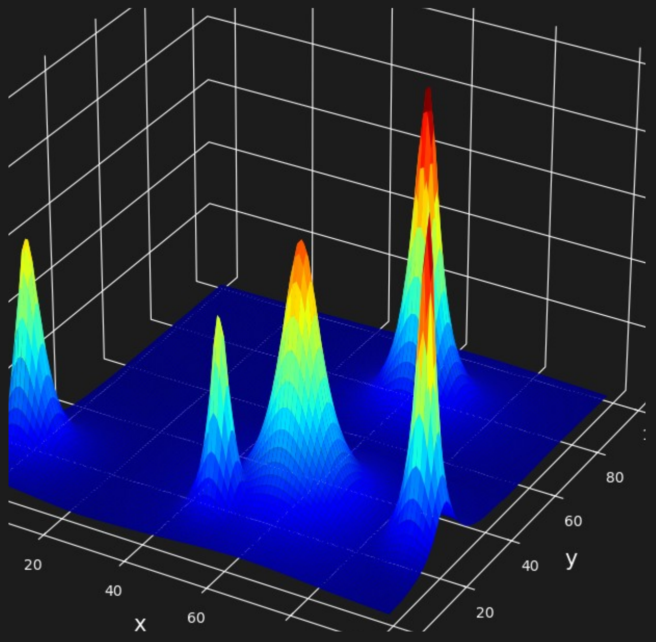
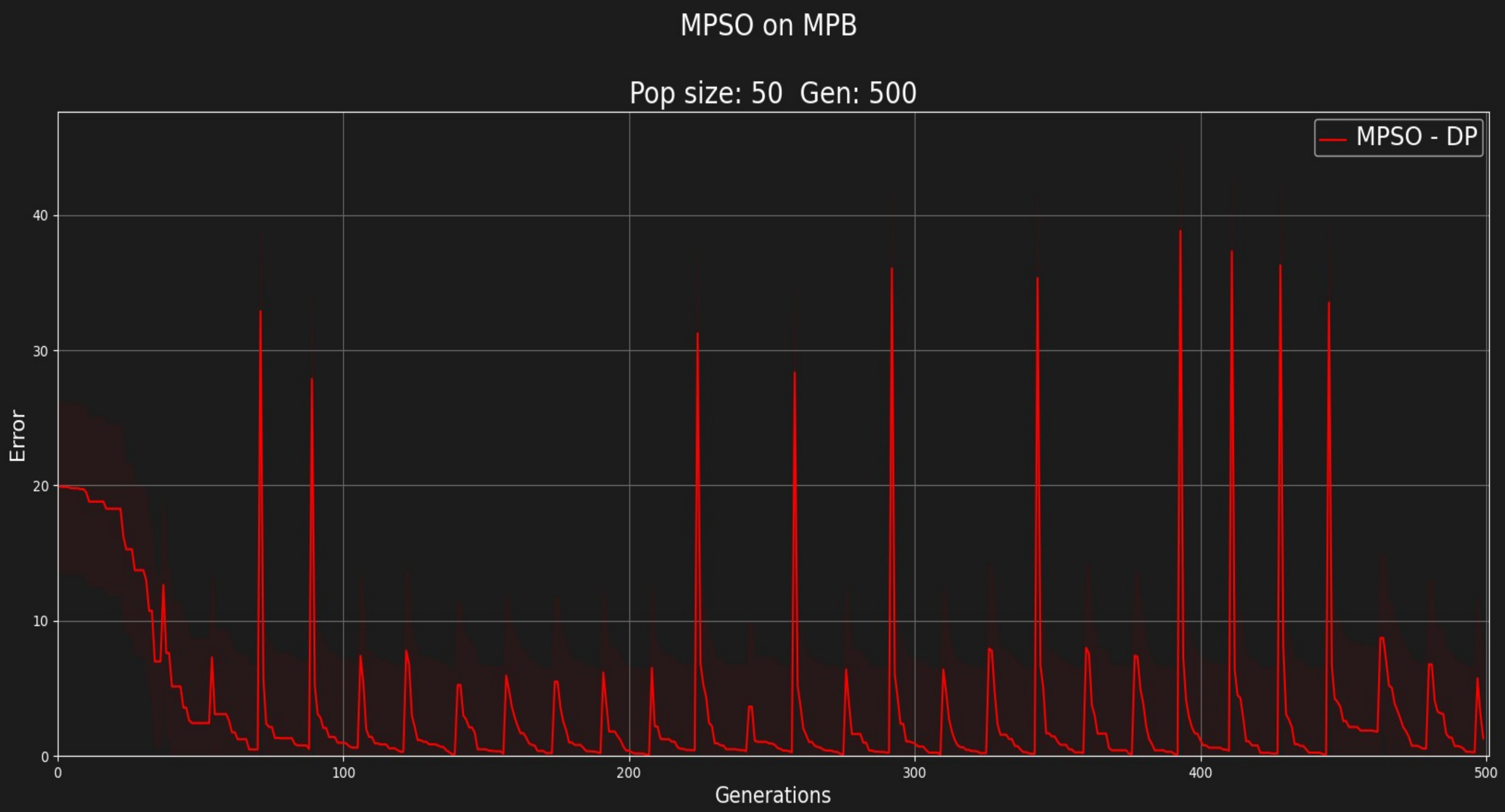
>> MPSO running in a dynamic problem (Moving Peak Benchmark)





> My research

> Gaps between academic research and real-world problems

>> No focus has been given in evaluate how well the dynamics characteristics of real-world problems are representatives in the academic problems(Rasmus K. Ursem et al. 2002)

>> The changes in real-world problems are generally not adequately characterized and/or understood(Jürgen Branke et al. 2005)

>> The relevance of the academic problems when applied to real-world problems does not correspond to the great efforts directed to them(Philipp Rohlfshagen and Xin Yao. 2008)

>> Current benchmarks for dynamic optimization are generally easy to solve and do not represent real problems (Trung Thanh Nguyen et al. 2020)

>> Currently, the test functions used to try to simulate a real dynamic environment still are not unified and mature (Hongjian Li and Geng Zhang. 2022)

> My research

> Future directions of the research

>> **Modeling the problem:**

>>> Model the real train control problem

>> **Evolutionary Dynamic Algorithms:**

>>> Further study the dynamic behavior of the algorithms as well as implement them to try to apply them to the real problem

>> **Benchmark:**

>>> With the results obtained, possibly create a benchmark with characteristics of a real problem

> End

> That’s all folks!

Thank you!

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