

# Stochastic optimization algorithms

## Lecture 10, 20200922

### Evolutionary algorithms: Applications (I)

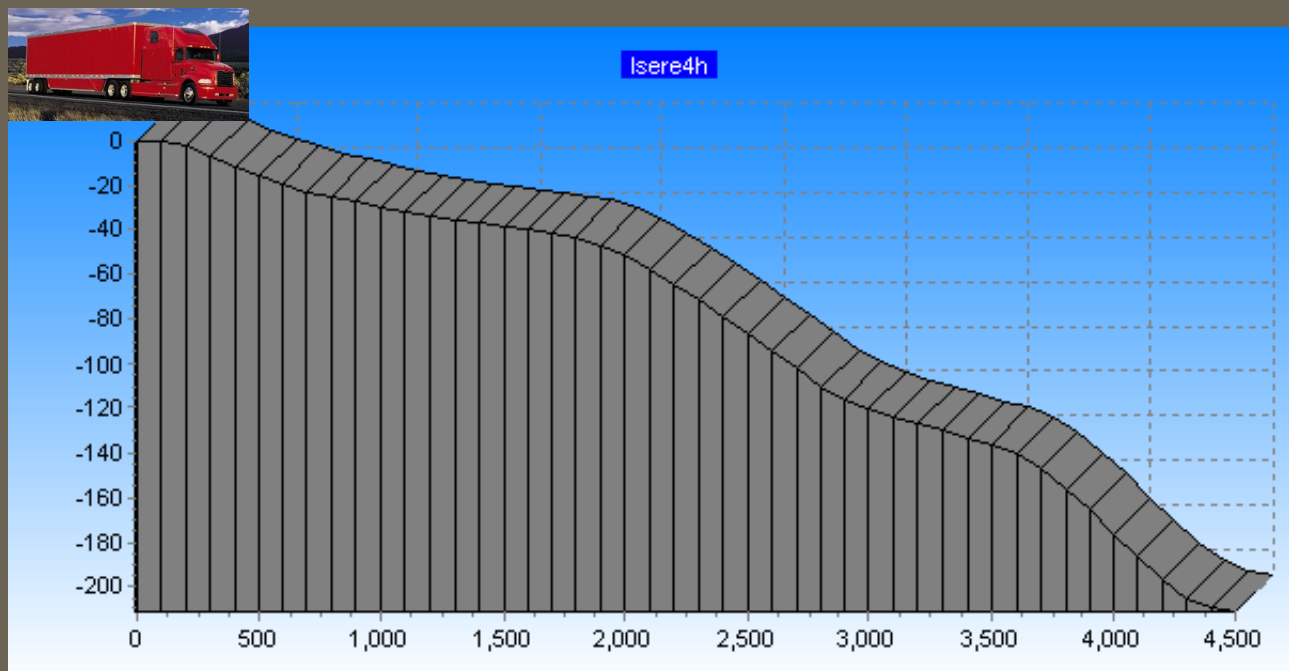
# Note: No lecture tomorrow!

- As per the original schedule for the course, there is no lecture tomorrow (Wednesday, Sept. 23<sup>rd</sup>).
- HP1 deadline today at 23.59.59.
- The next lecture will be on Friday, when I will also hand out HP2 (handin deadline: 20201014).

# Today's learning goals

- After this lecture you should be able to
  - Describe brake optimization in heavy-duty trucks
  - Describe multivehicle dynamic scheduling
  - Describe gait generation for robots using central pattern generators
- Note that there will be no exam questions regarding the details of any of the applications – they are meant as inspiring illustrations.
- In HP2, however, you will need to implement (a simplified version of) brake optimization.

# Truck brake system optimization



Application 1: Truck braking

# Brake systems

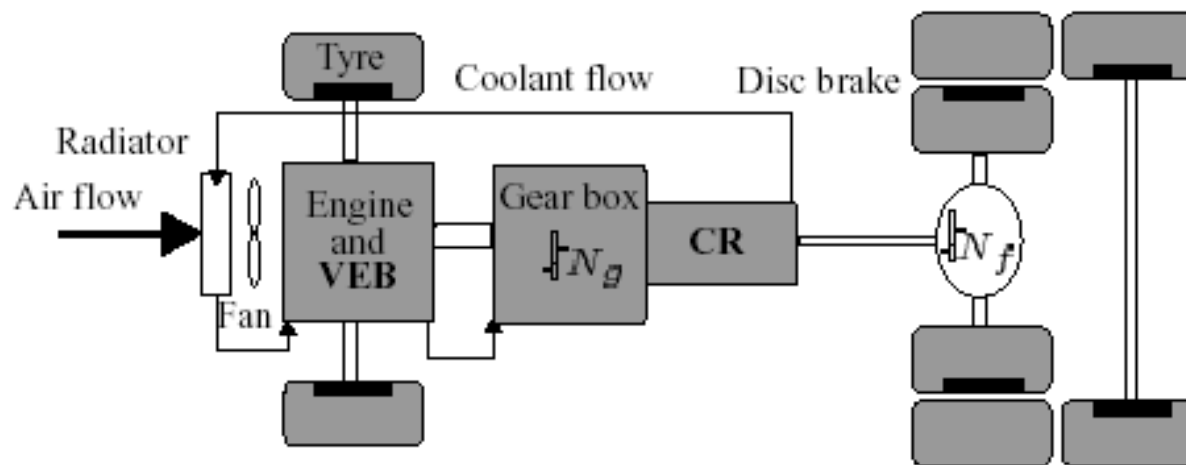


Fig. 1. Volvo retardation system

Application 1: Truck braking

# Braking strategy

- Downhill cruising: select a set speed and maintain it.
- Requires gear changes and activation of
  - pedal brakes (**foundation brakes**) and
  - **auxiliary brakes** (e.g. engine brake and compact retarder).
- Problem: too much usage of the foundation brakes => overheating => fading => no braking force => accident.
- Overheating of disc brakes: fading
- Overheating of auxiliary brakes: cooling system saturation

Application 1: Truck braking



# Possible solutions

- Use a lower set speed:
  - Leads to slower transportation => road congestion.
  - Potential economic drawback (slow delivery etc.).
- Use auxiliary brakes to save brake pads and discs:
  - Leads to high drive tyre wear => high maintenance cost.

# Another solution (our approach)...

- Find an optimal strategy for brake blending (usage of different brake combinations at different times) taking into account constraints such as ...
  - ... brake temperature
  - ... vehicle speed
  - ... engine speed etc.
- General reference:
  - [www.me.chalmers.se/~mwahde/AdaptiveSystems/Publications/LingmanWahdeAVEC2002.pdf](http://www.me.chalmers.se/~mwahde/AdaptiveSystems/Publications/LingmanWahdeAVEC2002.pdf)

Application 1: Truck braking





# Truck model

*Longitudinal motion equation:*

$$m\dot{v} = F_{\text{drive}} - F_{\text{air}} - F_{\text{roll}} - F_{\text{grade}} - F_{\text{aux}} - F_{\text{found}}$$

- $F_{\text{drive}}$  is assumed to be zero for downhill cruising.
- Equations for brake dynamics, air resistance etc.
  - See the paper (reference on previous slide).

Application 1: Truck braking

# Truck model

- Wear dynamics (needed for studying cost aspects of various strategies):

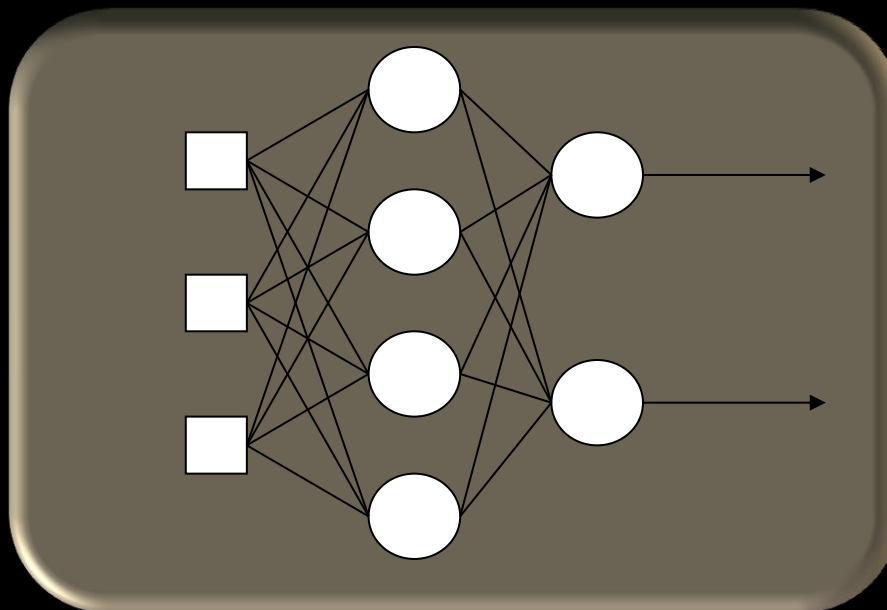
$$\dot{S}_{\text{pad}} = q_{\text{in}} S_0 e^{cT_1^{k_0}}$$

$$\dot{S}_{\text{tyre}} = v(a + b\tau_{\text{tyre}}^2 + c\tau_{\text{tyre}}^4 + d\tau_{\text{tyre}}^6)$$

Application 1: Truck braking

# Method

- Brake blending represented by FFNNs:



- Network size:  $5-N_h-4$  (Best  $N_h$  was found to be 7).

Application 1: Truck braking

# Method

- Inputs:
  - vehicle speed ( $v$ ),
  - current road slope ( $\alpha$ ),
  - disc brake temperature ( $T_1$ ),
  - coolant temperature ( $T_{\text{coolant}}$ ),
  - engine speed ( $v_E$ ).

Application 1: Truck braking



# Method

- Outputs:
  - (1) total retardation force request,
  - (2) gear choice (inc, dec, unchanged),
  - (3) fraction of braking force taken from foundation brakes,
  - (4) split of auxiliary braking force from VEB (engine brakes) and CR (compact retarder).

Application 1: Truck braking



# Method

- Constraints:
  - Disc temperature  $T_1 < 500$  degrees (C),
  - Vehicle speed  $v > 5$  m/s,
  - Vehicle speed  $v < 25$  m/s,
  - Engine speed  $v_E < 2300$  rpm,
  - Engine speed  $v_E > 600$  rpm,
  - Total time  $< (\text{for example}) 200$  s

Application 1: Truck braking



# Method

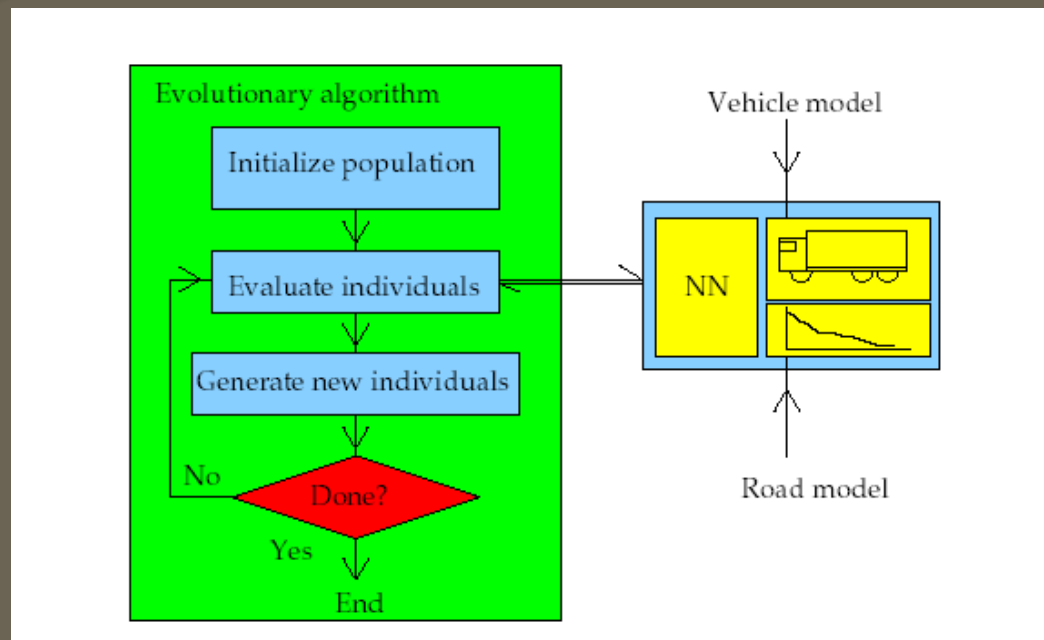
- Feedforward network, *but* no input-output pairs (for every instant).
- Use a genetic algorithm instead.
- Only parametric optimization was used.
- The (minimum) number of neurons in the middle layer was determined using trial-and-error.
- Typical parameters:
  - Population size = 100,
  - Number of generations = 1000.

Application 1: Truck braking



# Method

- Fitness measure: Distance travelled in a given maximum time (evaluation terminated if constraints violated).



Application 1: Truck braking



# Road profiles

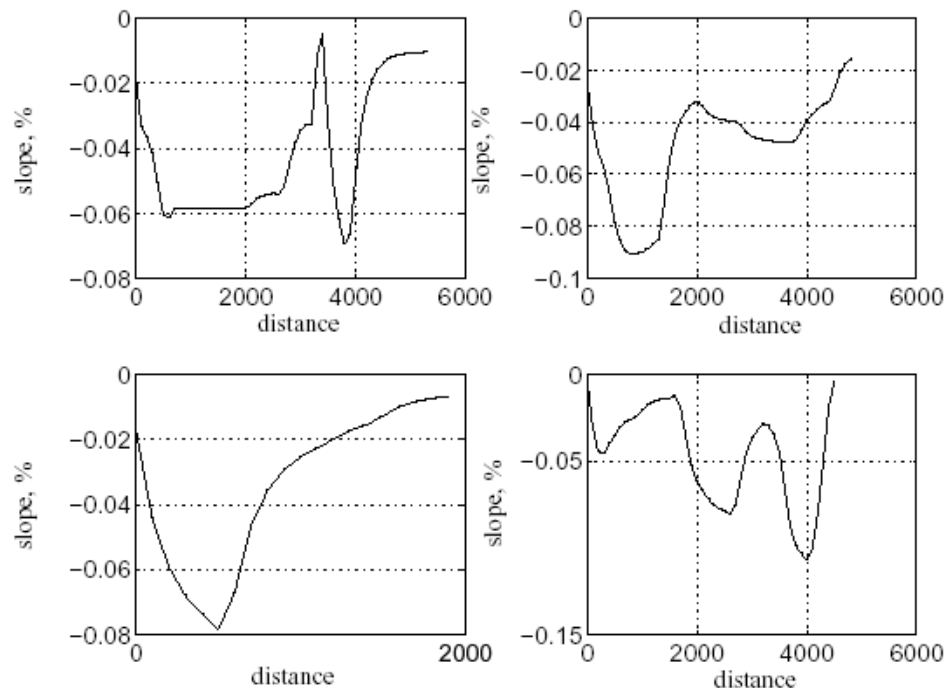


Fig. 5. Example of measured road profiles used. French alps, Isère 1-4

Application 1: Truck braking

# Result (example)

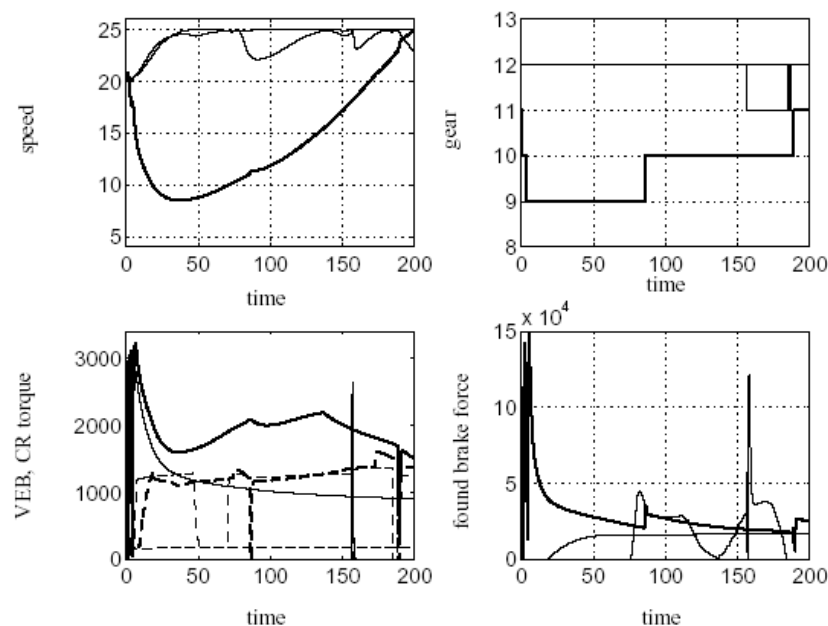
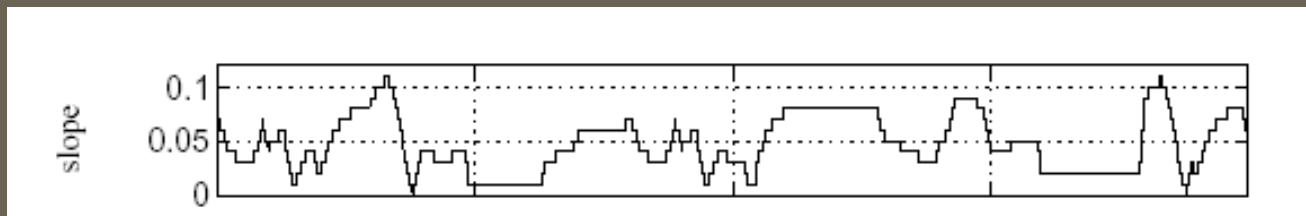


Fig. 3. Optimal blending for high mean speed on 3 roads.  
 Thick solid line: 10% constant slope, Medium solid line: Isère 4 road, Thin solid line: 5% constant slope

Application 1: Truck braking

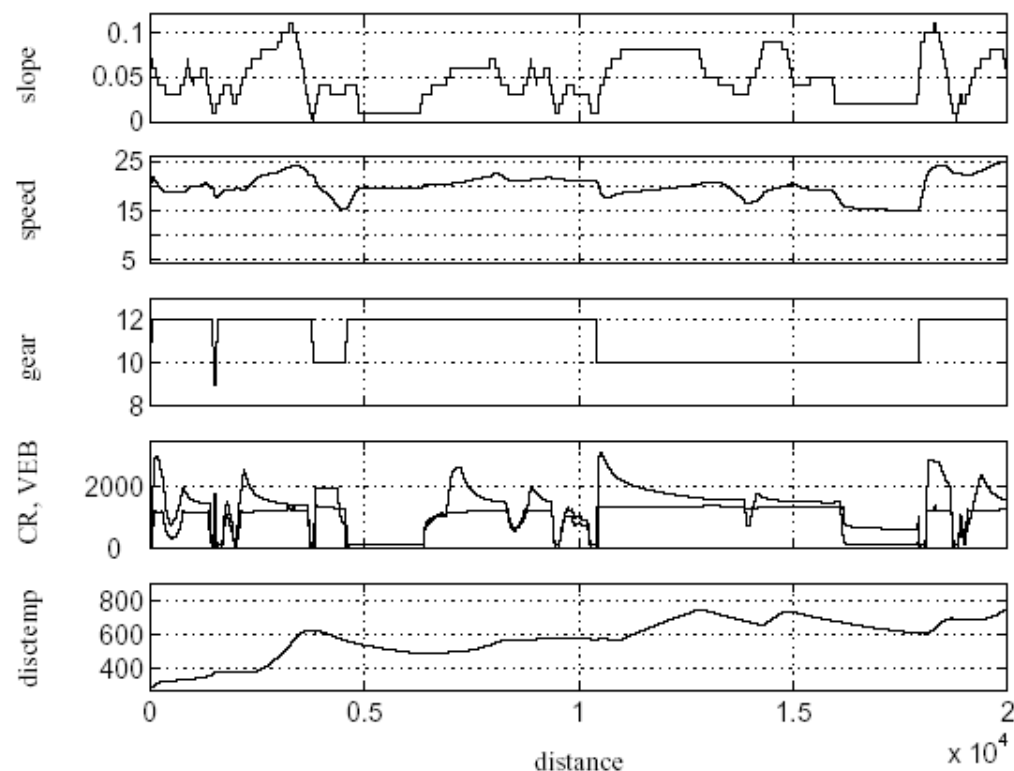
# Problem

- Adaptation to specific conditions in the training roads!
- Solution: Construct a long, artificial road, containing as many relevant aspects as possible (using parts from the French alps (Isère), and Kassel hills in Germany).



Application 1: Truck braking

# Result (example)



Application 1: Truck braking

# Generalization (validation set)

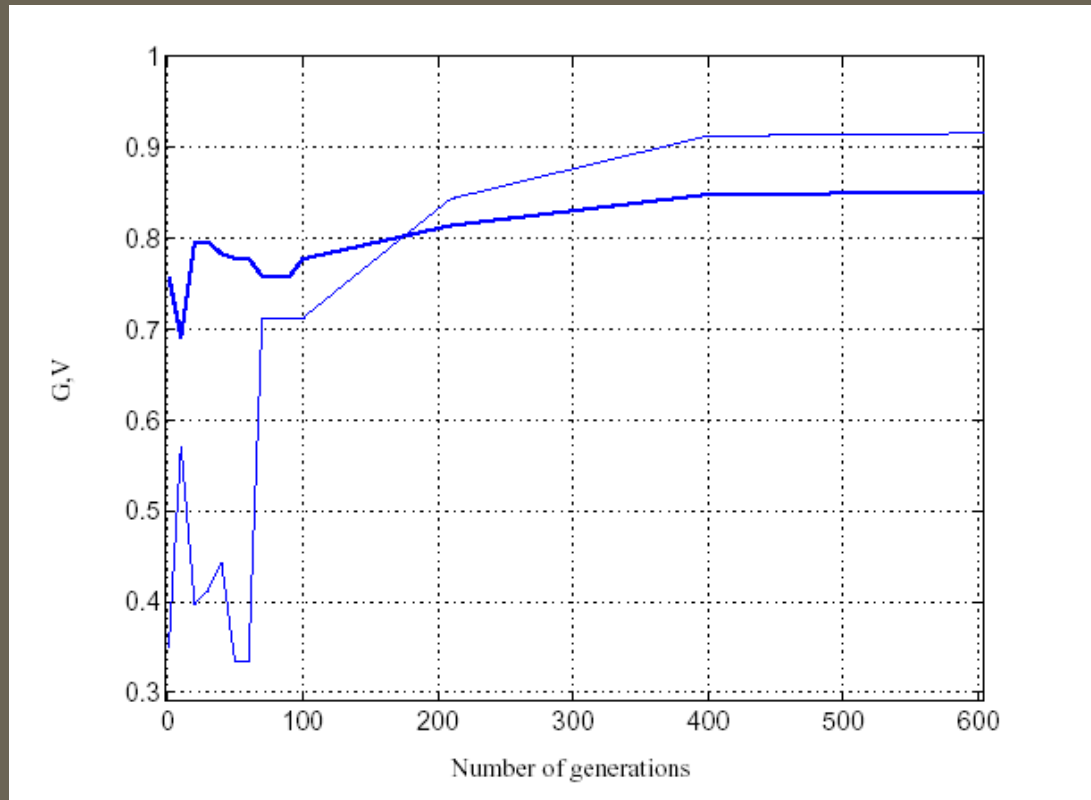
- Two measures were defined:

$$G = \frac{1}{N_r} \sum_{i=1}^{N_r} \frac{d_i}{L_i}; \quad V = \frac{1}{N_r v_{\max}} \sum_{i=1}^{N_r} \bar{v}_i$$

- $N_r$  (the number of test roads) was set to 14.

Application 1: Truck braking

# Generalization (validation set)



Application 1: Truck braking

# Today's learning goals

- After this lecture you should be able to
  - Describe brake optimization in heavy-duty trucks
  - Describe multivehicle dynamic scheduling
  - Describe gait generation for robots using central pattern generators



# Dynamic multivehicle scheduling

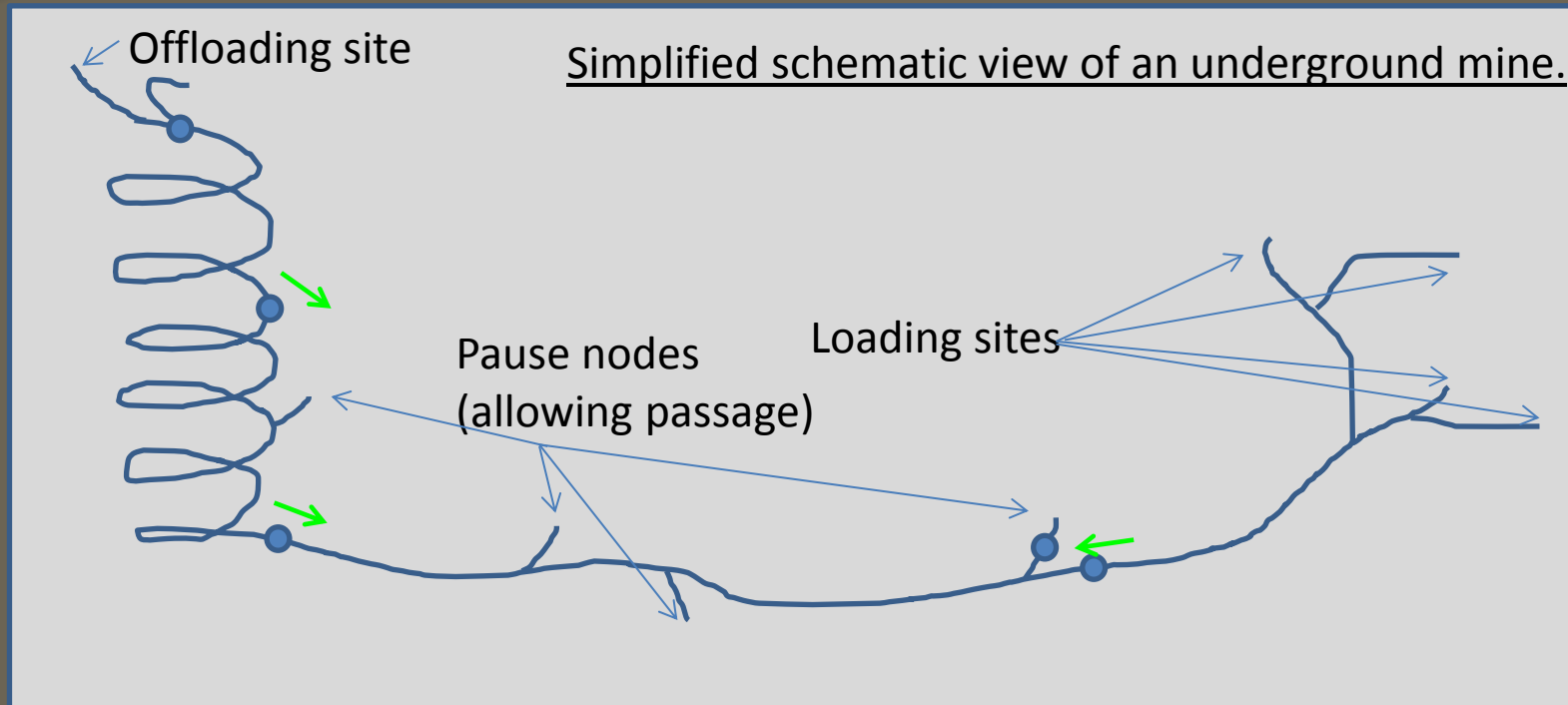
- Dynamic scheduling and path planning for underground mines is a complex task.
- Even though some mines do use autonomous vehicles, the trajectory planning (path + timing) is usually done by hand, in a suboptimal manner.
- In our work, we have developed a method for fully autonomous mining, involving GA-based dynamic trajectory planning.

Application 2: Dynamic multivehicle scheduling





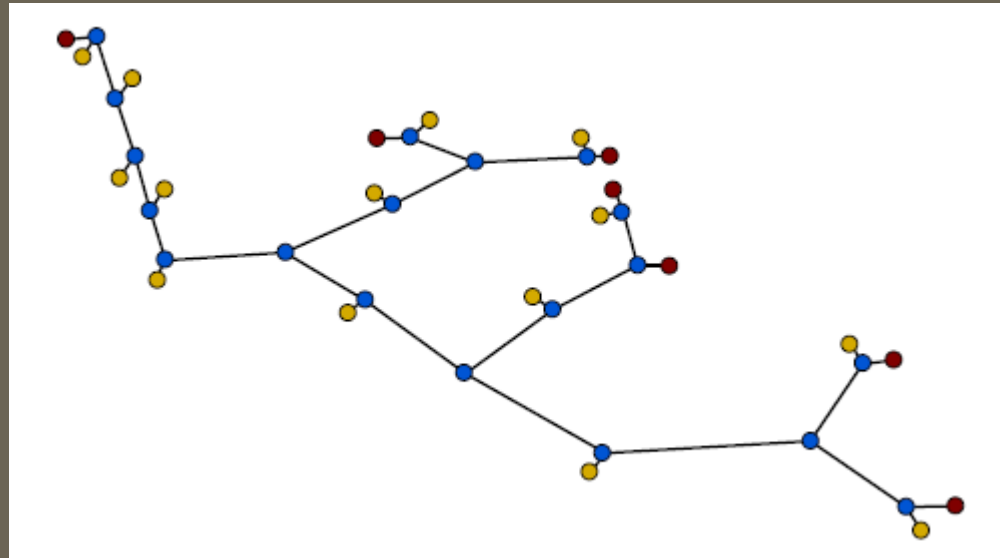
# Underground mines



- The spiral path to is a significant bottleneck!

Application 2: Dynamic multivehicle scheduling

# Underground mines



- Topological representation.
- Red = terminal, Blue = transit, Yellow = pause

# Constraints and goal

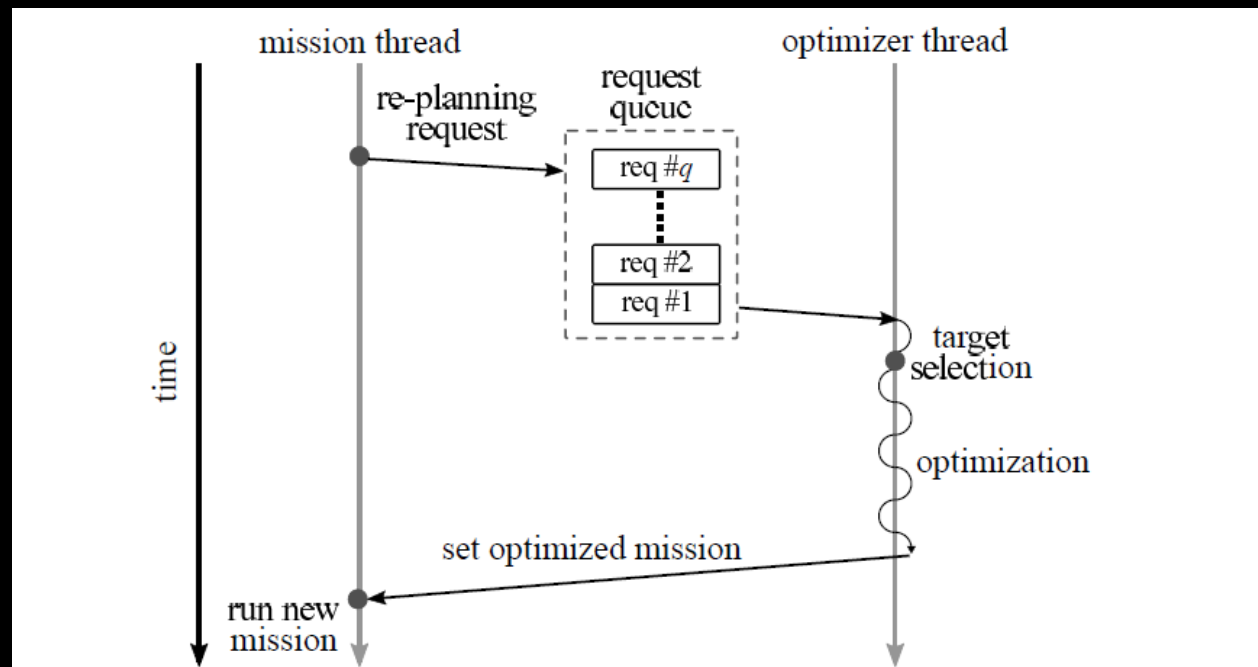
- Constraints
  - Collisions (and near-collisions) must be avoided.
  - Speed settings (in this case): 30 km/h outbound, 20 km/h inbound except on the spiral path (10 km/h).
  - Inbound vehicles (going towards the offloading station) are not allowed to stop until they reach their target.
  - Outbound vehicles (going from the offloading station) are allowed to stop at pause nodes.
- Goal
  - Maximize the number of round trips per unit time.

# Addition problem description

- Vehicles that arrive at a terminal must either offload or load material.
- The time required for doing so varies from instance to instance.
- Once these operations have been completed, the vehicle *requests* a plan to proceed either to a loading station (if empty) or to the offloading station (if full).

# Addition problem description

- Requests can be made at any time and in any order.
- Thus, a queue is maintained:

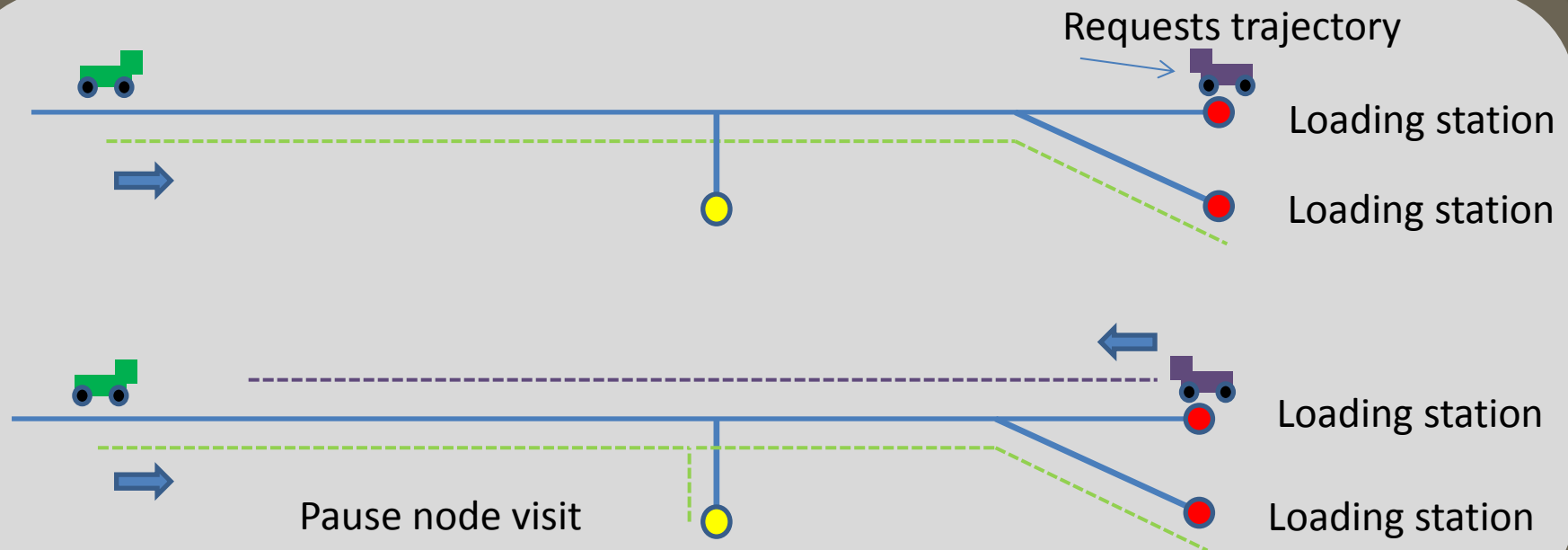


Application 2: Dynamic multivehicle scheduling

# Trajectory optimization

- When the optimizer is running, its goal is to generate a trajectory (path and timing) for the vehicle that requested the optimization.
- Doing so may also involve modifying the trajectories of other vehicles.
- Note: The main difficulty is not path generation but the *timing* (scheduling), making sure to avoid collisions while maximizing efficiency (minimizing delays).

# Trajectory optimization



# Trajectory optimization

- Problem: The optimization procedure is not instantaneous. Therefore, the optimizer must account for the motions (of other vehicles) that occur *during* optimization.
- In other words, the optimizer must make sure to maintain causality, only modifying decisions that will (still) be in the future when the optimizer is done.
- Additional problem: In some cases the optimizer might fail (the solution might not even *exist*, in some situations).
- Thus, the optimization problem is very complex.

Application 2: Dynamic multivehicle scheduling





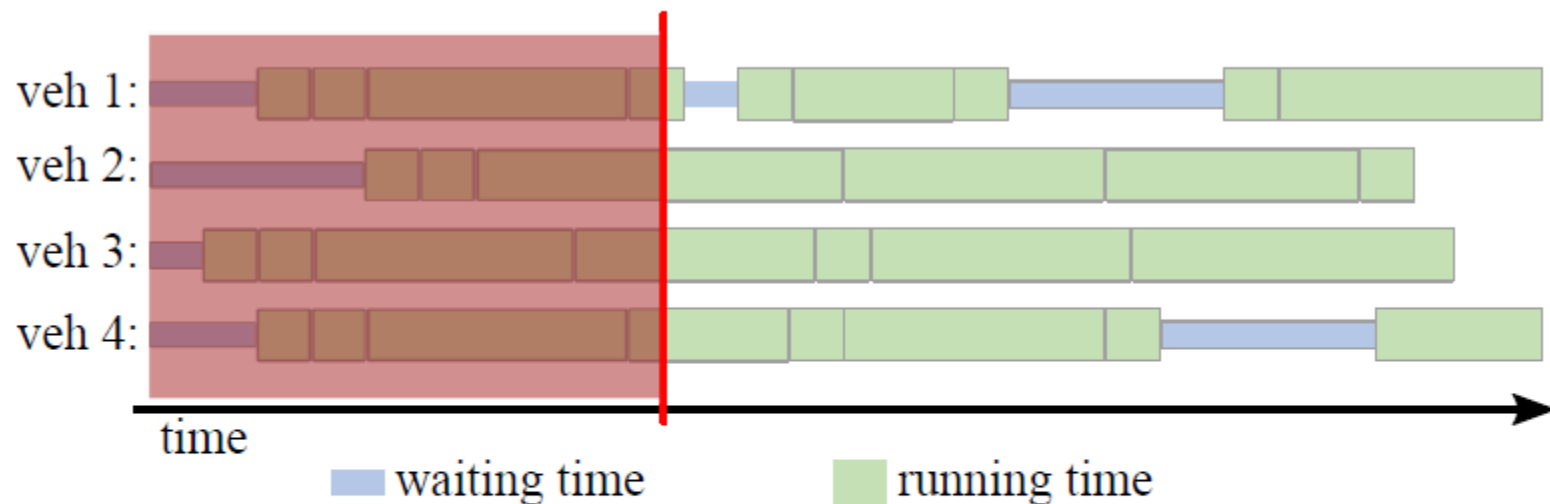
# Trajectory optimization

- We have used a (modified) genetic algorithm to optimize the trajectories.
- Each vehicle is associated with a mission  $M$ , consisting of a sequence of mission items that, in turn define an initial stop time ( $=0$  except for the (i) the start node in a mission and (ii) at pause nodes, where applicable).
- The fleet mission is the complete set of (current) missions, one for each vehicle.

Application 2: Dynamic multivehicle scheduling



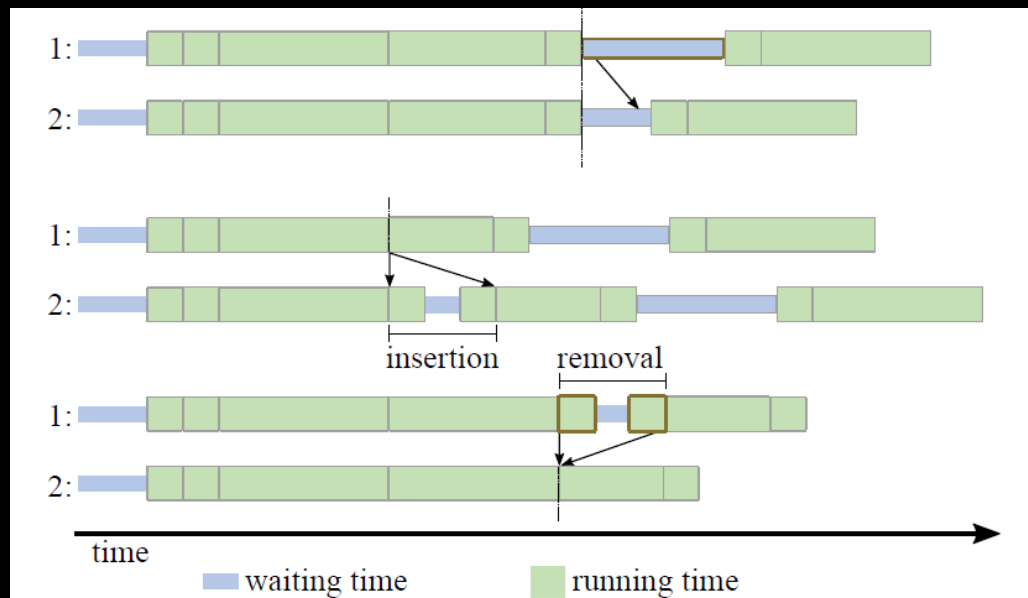
# Graphical representation of missions



**Fig. 3** A fleet mission for a fleet of four vehicles. In this particular case, the top and bottom vehicles are outbound (moving away from the offloading station), whereas vehicles two and three are inbound. The red vertical line indicates the current elapsed time. At this point, all four vehicles are moving, but the first vehicle (the top row) will soon reach a pause node where it will make a brief stop (indicated by the light-blue box), allowing an incoming vehicle to pass.

# Trajectory optimization

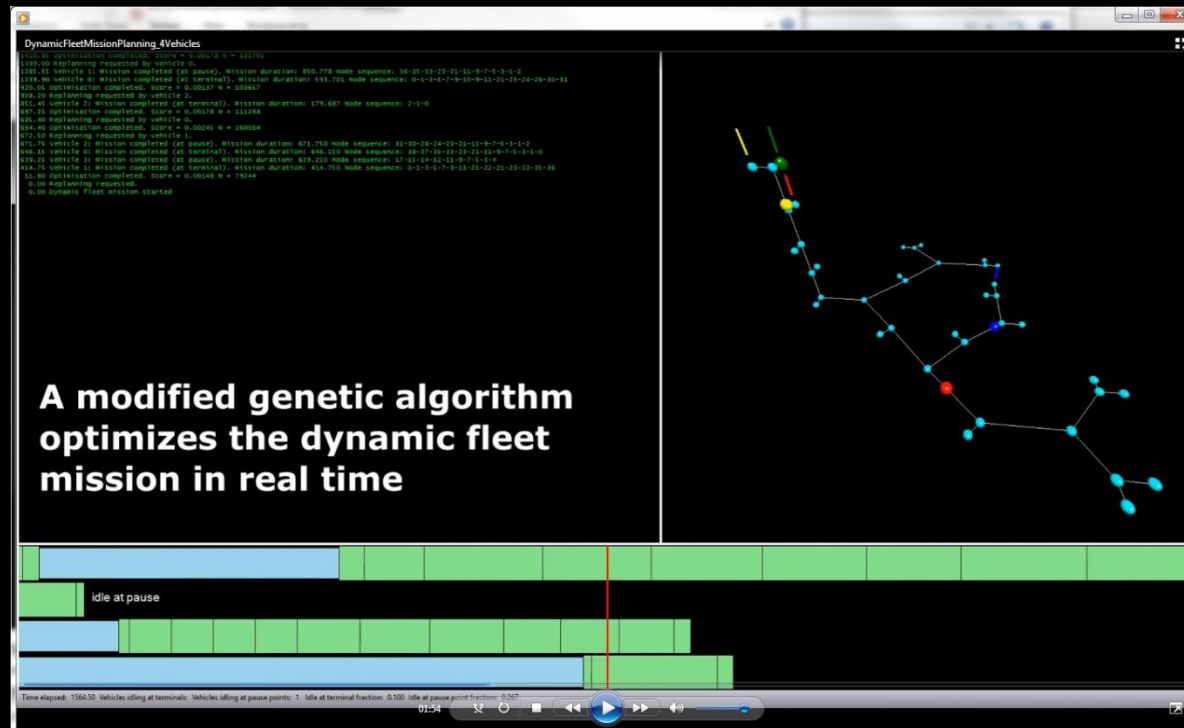
- The GA can (i) change initial stop times, (ii) insert pause node visits (for outbound vehicles) and (iii) remove pause node visits (also for outbound vehicles):



## Results (very brief summary)

- The GA is highly efficient at optimizing trajectories, beating other methods for this kind of map (with bottleneck).
- The number of completed traversal (per vehicle) drops by only 27% as the number of vehicles is increase by 150%.
- Idle times (at terminals and pause nodes) are kept to a minimum.
- For more details, see our paper: Wahde, M., Bellone, M., and Torabi, S.: [\*A method for real-time dynamic fleet mission planning for autonomous mining.\*](#)

# Video



See the video at <http://www.me.chalmers.se/~mwahde/research/mining/videos.html>

Application 2: Dynamic multivehicle scheduling

# Today's learning goals

- After this lecture you should be able to
  - Describe brake optimization in heavy-duty trucks
  - Describe multivehicle dynamic scheduling
  - Describe gait generation for robots using central pattern generators



# Evolutionary robotics

- Subfield of robotics, in which evolutionary algorithms (EAs) are used for generating robotic brains (or bodies, or both).
- Representation of a robotic brain: Typically in the framework of **behavior-based robotics (BBR)**.
- In BBR, robotic brains are built in a bottom-up fashion, from simple behaviors.
- This approach (BBR + EA) has been applied in many robotics tasks.

Application 3: Robot gaits



# Gait generation for humanoid robots

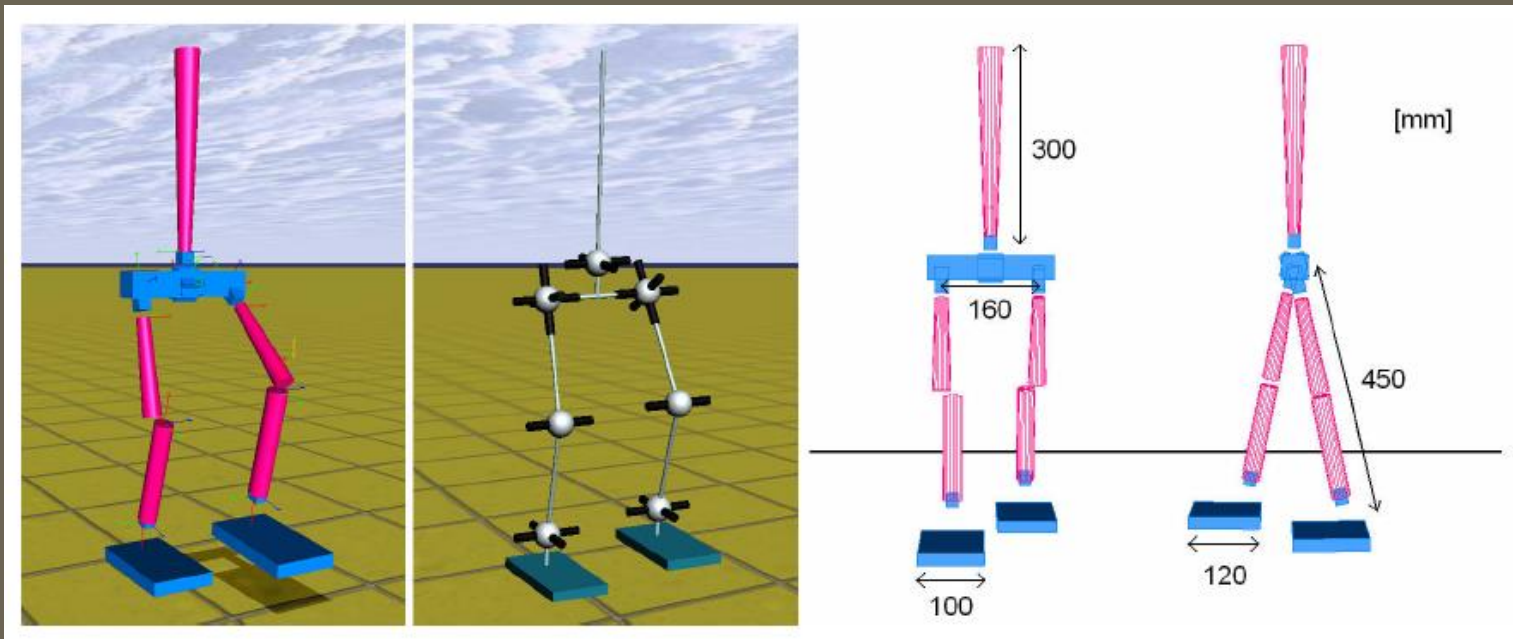
- In this project, the aim was to evolve the gait (walking pattern) for a humanoid robot.
- One of the papers resulting from this project can be found [here](#).

Application 2: Robot gaits





# Evolution of bipedal gaits



Application 3: Robot gaits

# Central pattern generators

- Central pattern generators (CPGs) are neural circuits capable of producing oscillatory output given tonic (non-oscillating) input.
- CPGs have been extensively studied in animals:
  - simple animals: lamprey, salamander
  - complex animals: cats
- Observations support the notion of CPGs in humans: Treadmill training of patients with spinal cord lesion.

Application 3: Robot gaits



# The Matsuoka oscillator

$$\begin{aligned}\tau_u \dot{u}_i &= -u_i - \beta v_i + \sum_{j=1}^n w_{ij} y_j + u_0, \\ \tau_v \dot{v}_i &= -v_i + y_i, \\ y_i &= \max(0, u_i),\end{aligned}$$

$u_i$  = inner state

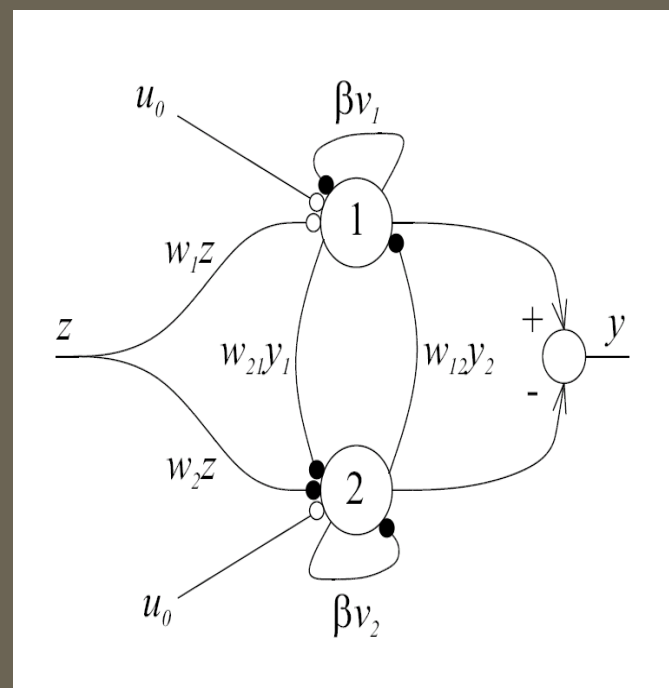
$v_i$  = degree of self inhibition

$\tau_u$  and  $\tau_v$  = time constants

$u_0$  = bias (tonic input)

$w_{ij}$  = connection weights

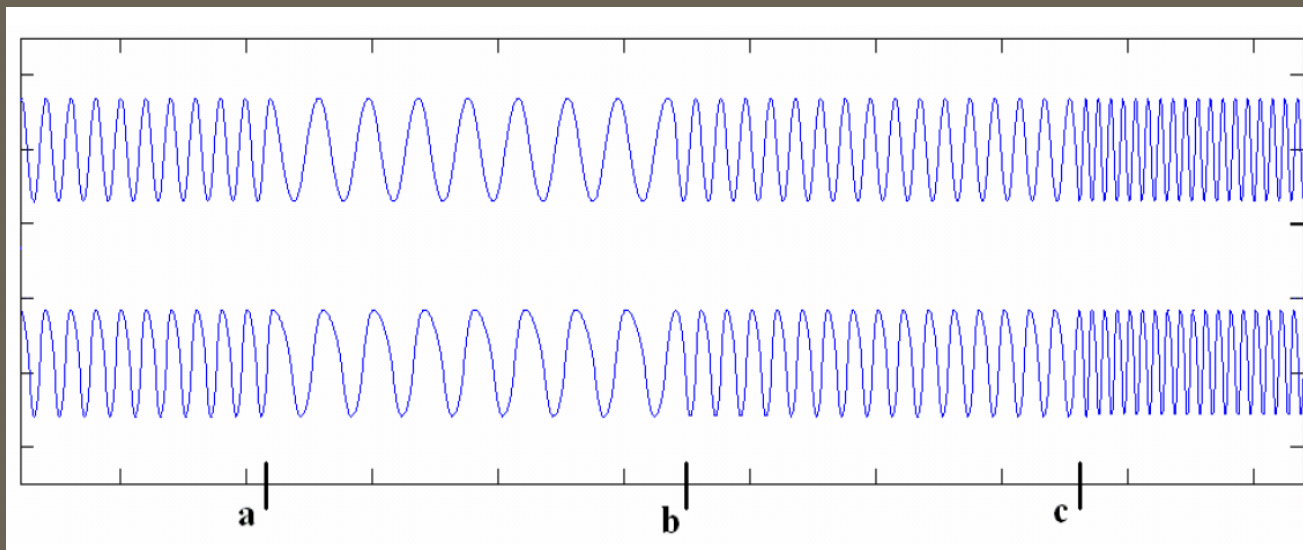
$y_i$  = output



Application 3: Robot gaits

# The Matsuoka oscillator

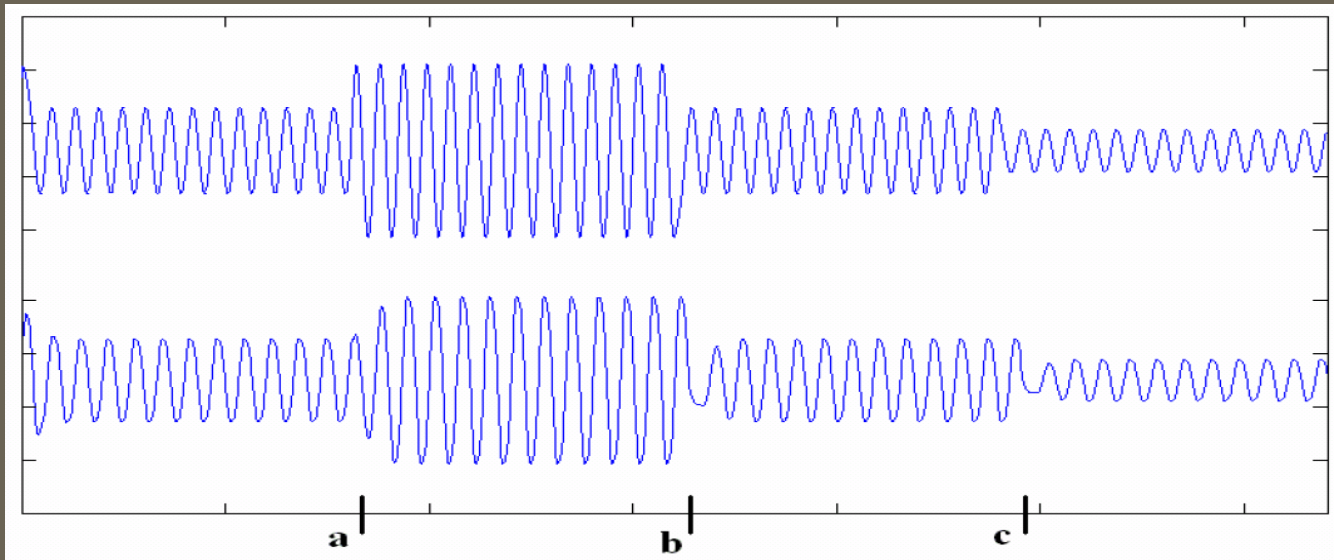
- Frequency variation when the time constants  $\tau_u$  and  $\tau_v$  are varied.



Application 3: Robot gaits

# The Matsuoka oscillator

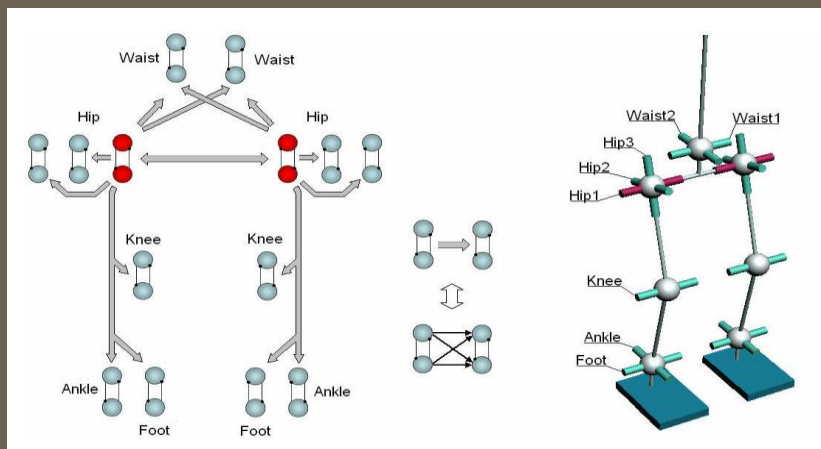
- Amplitude variation when the bias  $u_0$  is varied.



Application 2: Robot gaits

# CPG network

- An arrow indicates the *possibility* of a connection:

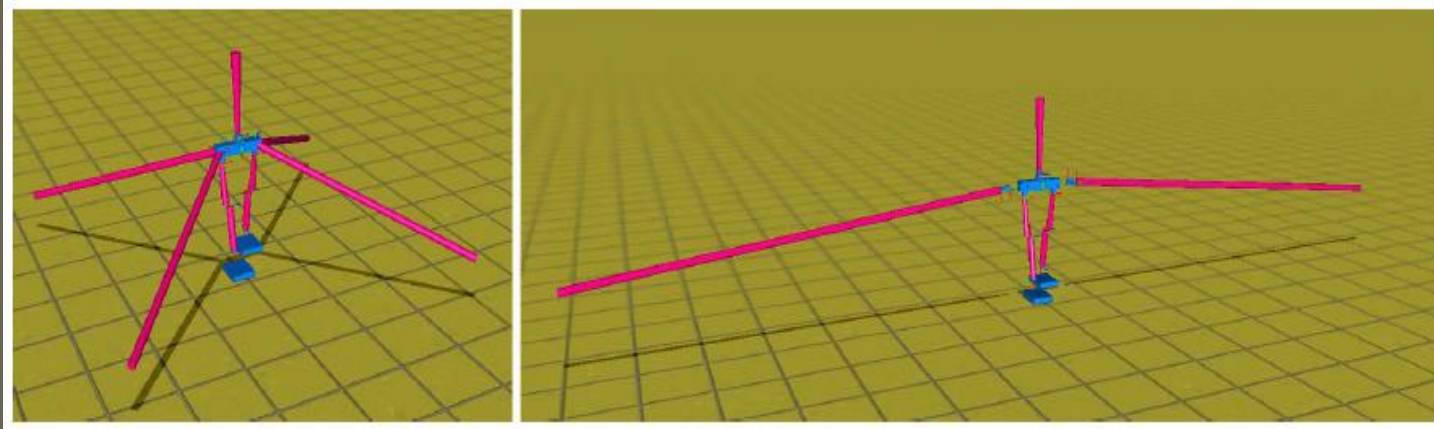


- The CPG network was evolved using a GA.
- Fitness: Distance walked.

Application 2: Robot gaits

# Support structure

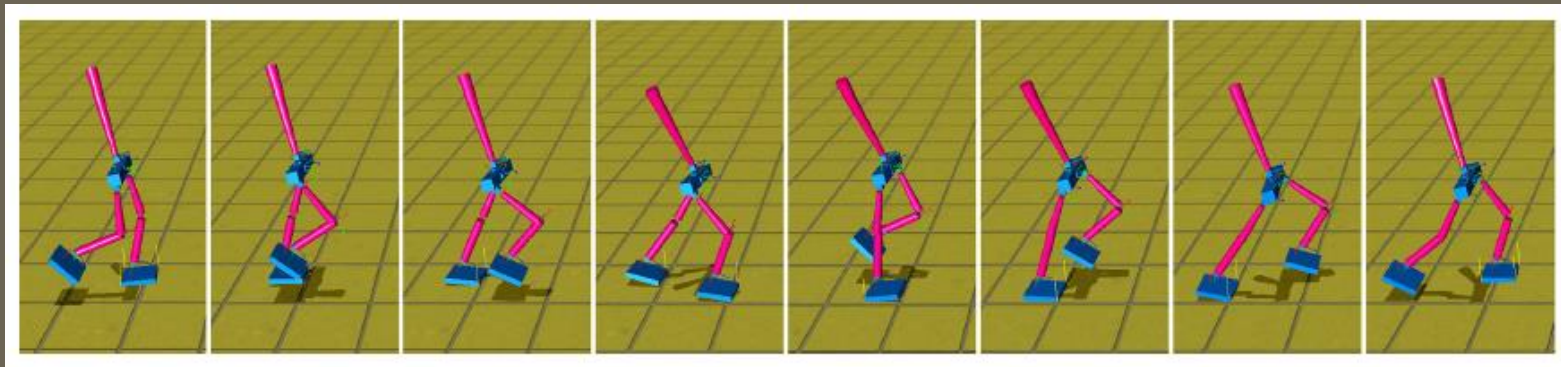
- A mass-less support structure was used with the robot to force natural, upright gaits.
- Helps the robot to balance in the initial stage
- Forces it to walk in an upright manner



Application 2: Robot gaits



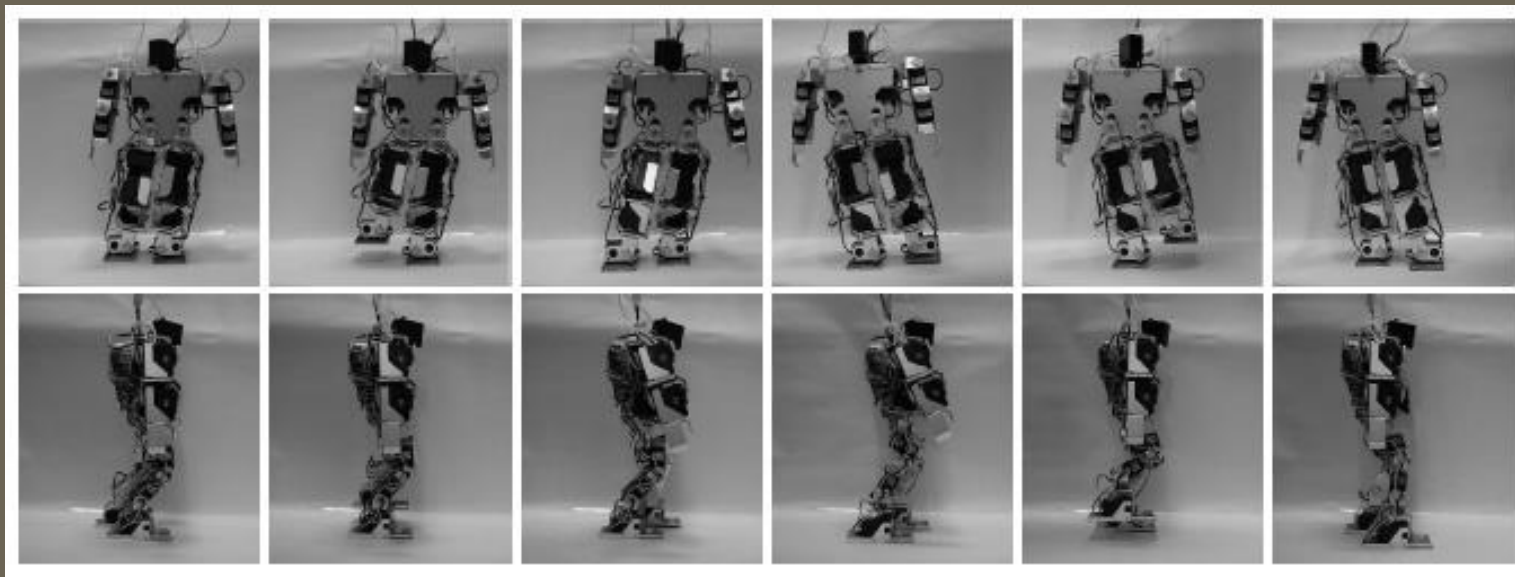
# Results (Example)



Application 3: Robot gaits



# Evaluation in physical robots



Application 2: Robot gaits

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