IEEE AEROSPACE CONFERENCE
YELLOWSTONE CONFERENCE CENTER, BIG SKY, MONTANA,
MAR 3 – MAR 10, 2018

Evolutionary Algorithms for Near-optimum Detection of Multi-beam Satellite Signals

Claudio Sacchi[(*)], Talha Faizur Rahman[(**)], Cosimo Stallo[(***)], Marina Ruggieri[(***)]

[(*)] *University of Trento, Dept. of Information Engineering and Computer Science (DISI), Trento (Italy)*

[(**)] *Center for Advanced Studies in Telecommunications (CAST), Institute of Information Technology (COMSAT), Islamabad (Pakistan)*

[(***)] *University of Rome, Tor Vergata, Department of Electronic Engineering, Rome (Italy)*

Outline

- ***Problem statement and motivations;***
- ***System description;***
- ***Fundamentals on multi-beam detection;***
- ***Evolutionary algorithms for ML multi-beam detection;***
- ***Simulation results;***
- ***Conclusion and future work;***
- ***Essential bibliography;***
- ***Contact information.***

Problem statement and motivations (1)

- Broadband multi-beam satellite systems will be based on aggressive frequency reuse policies in order to boost the data-rate to terabit/sec. values;

- Aggressive frequency reuse policies forecast that adjacent beams share the same frequency band;

- In such a framework, the problem of multi-beam interference rejection should be addressed in efficient manner;

- If the number of interfering beams and/or the number of levels of digital modulation are high, optimum Maximum-Likelihood (ML) detection becomes computationally prohibitive.

Problem statement and motivations (2)

- Suboptimal multi-beam detection techniques should be, therefore, considered;

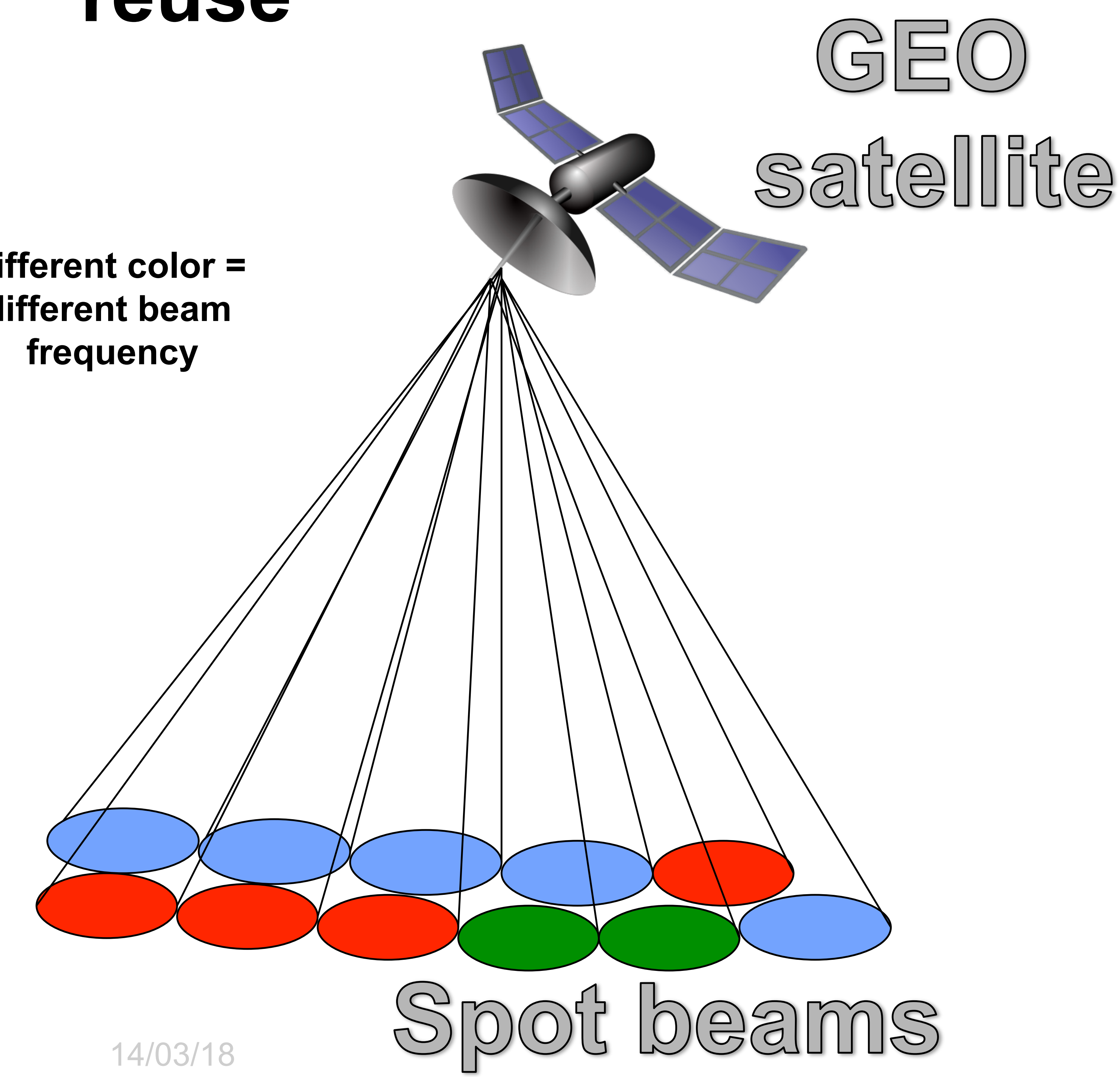
- In our paper, we consider near-optimum multi-beam detection approaches, based on evolutionary optimization algorithms, namely:
  - Genetic algorithms (GAs);
  - Particle Swarm Optimization (PSO).

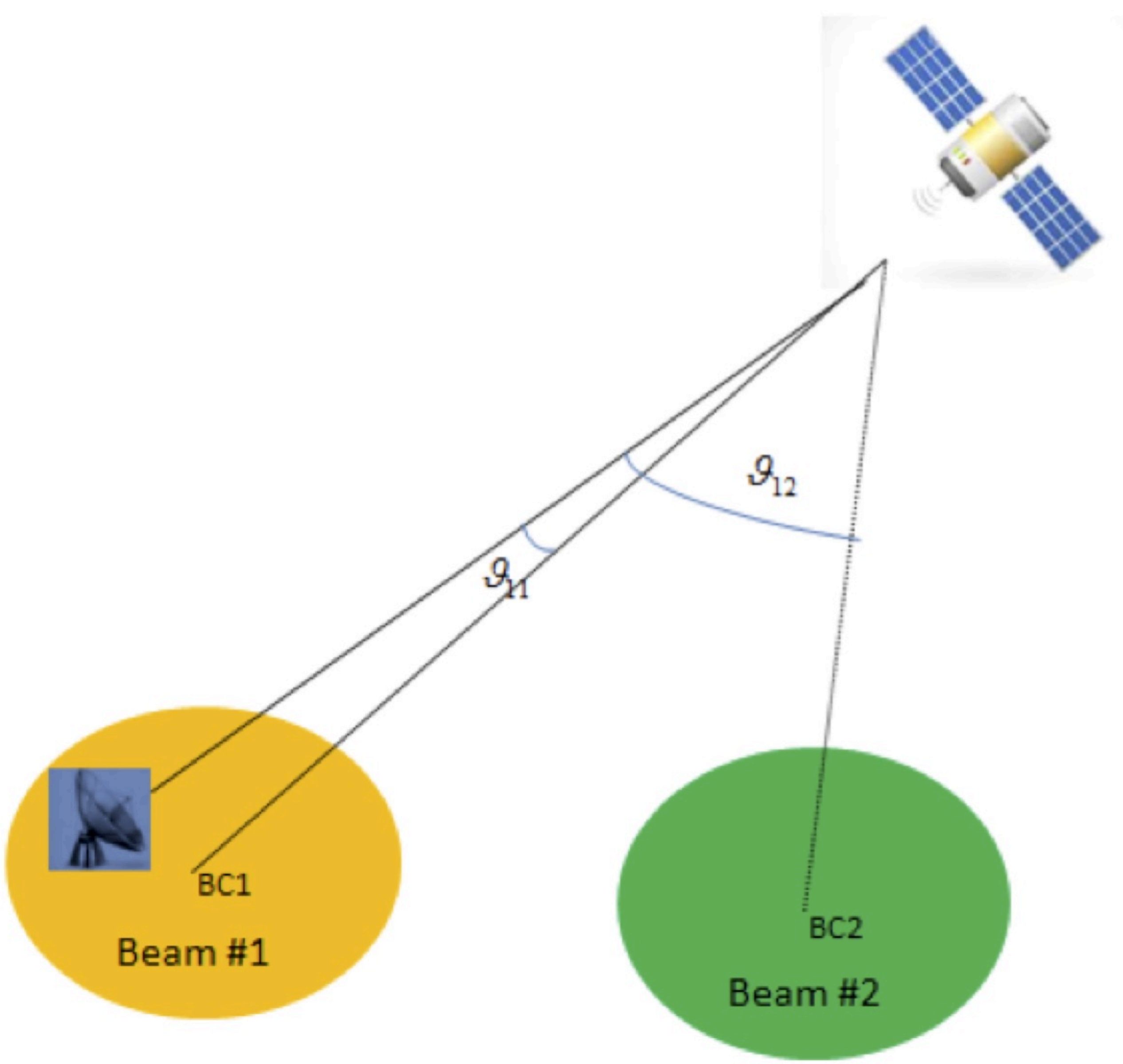
- The objective is to provide near-optimum detection with affordable computational burden.

System description (1)

- **Multi-beam satellite systems with aggressive frequency reuse**

Different color = different beam frequency



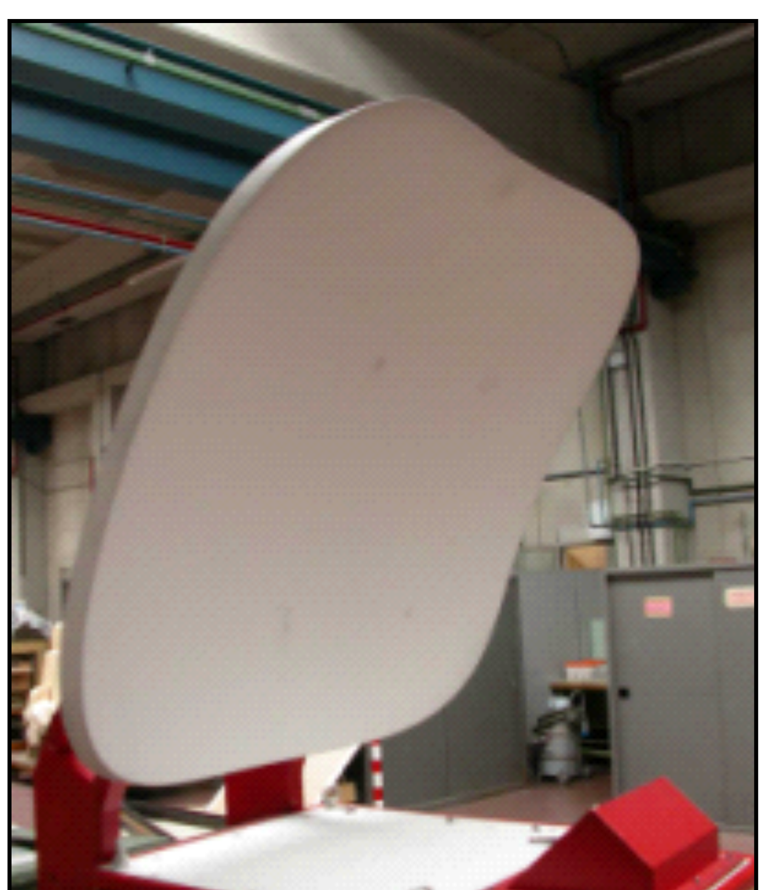


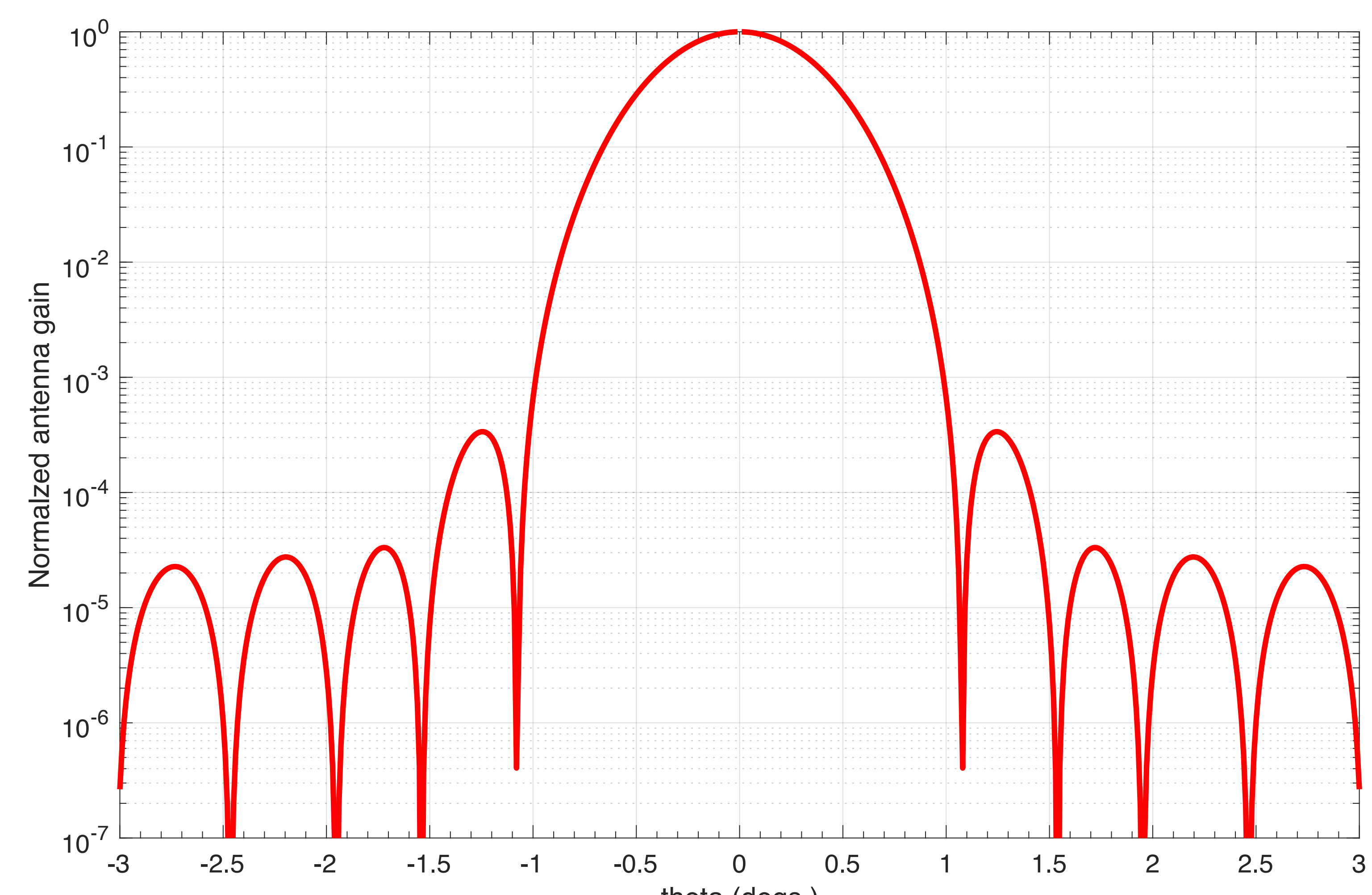
Beam angles

System description (2)

- **The adopted multi-beam antenna system**
  - **We consider, according to[1], a Single-Feed per Beam Network (SFBN) antenna system. Antenna gain related to beam *j* is given as follows[2]:**

$$G_j(u) = G_{M,j}\frac{(p+1)(1-T)}{(p+1)(1-T)+T}\cdot\left(2\frac{J_1(u)}{u}+2^{p+1}p!\frac{T}{1-T}\frac{J_{p+1}(u)}{u^{p+1}}\right) \qquad u = \pi\frac{D_a}{\lambda_c}\sin\theta$$





Radiation pattern of SFBN antenna for T=0.9, p=2, f_c=20 GHz, D_a=1.5 m.

System description (3)

- **Beam angle computation**
  - **The beam angles have been computed according to the analytical formulation shown in[3]**

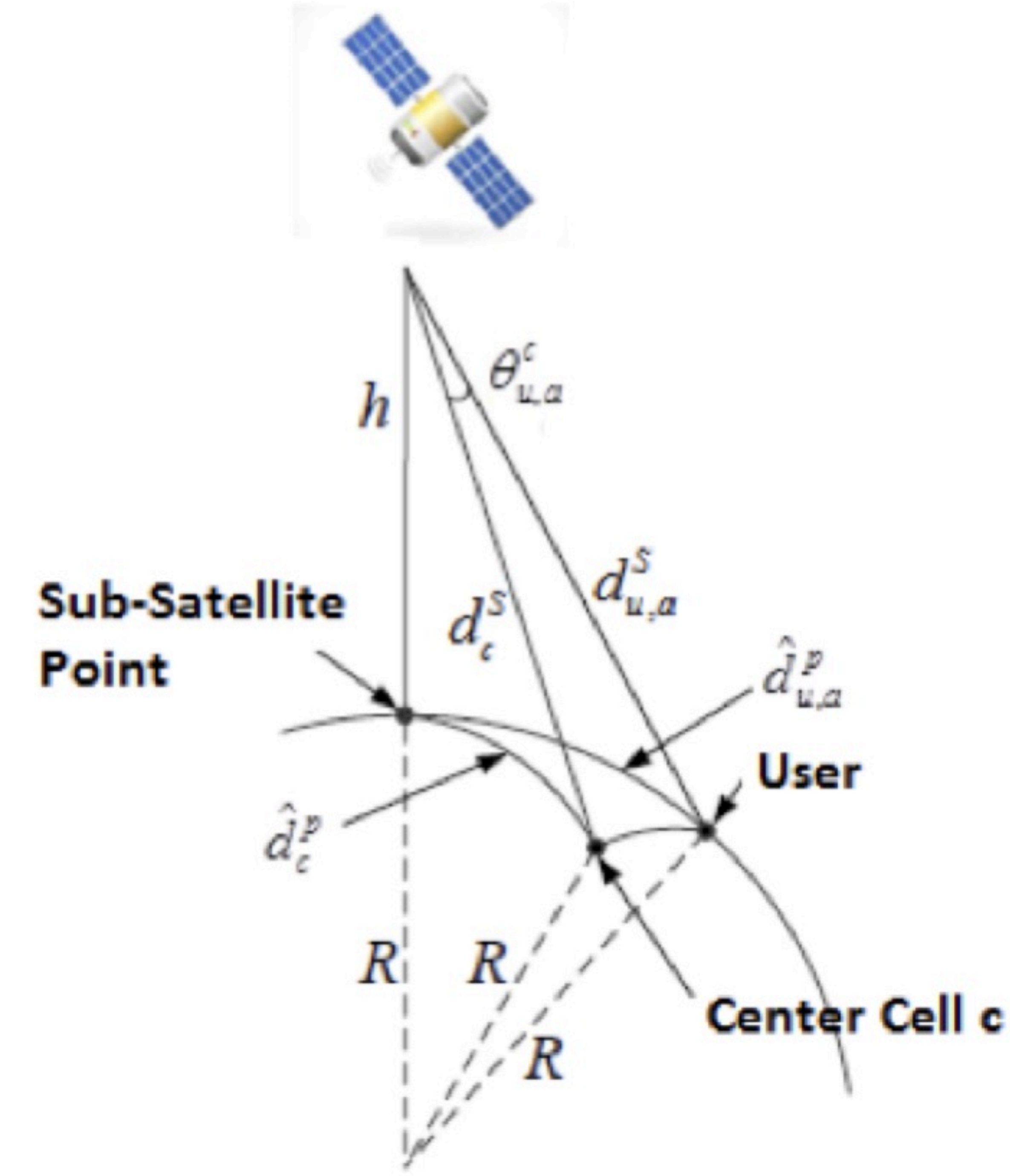
<u>NOTATION</u>: user *u*, in cell *a*, of centre *c*

$$\theta^{c}_{u,a} = ar\cos\left\{\left(d^{S}_{c}\right)^{2} + \left(d^{S}_{u,a}\right)^{2} - 2R^{2}\left[1-\cos\left(\frac{\hat{d}_{u,c}}{R}\right)\right]\cdot\left(2d^{S}_{c}d^{S}_{u,a}\right)^{-1}\right\}$$

<u>WHERE</u>:

$$d^{S}_{c} = \left\{h^{2} + 2R\left(R+h\right)\left[1-\cos\left(\frac{\hat{d}^{p}_{c}}{R}\right)\right]\right\}^{\frac{1}{2}}$$

$$d^{S}_{u,a} = \left\{h^{2} + 2R\left(R+h\right)\left[1-\cos\left(\frac{\hat{d}^{p}_{u,a}}{R}\right)\right]\right\}^{\frac{1}{2}}$$



Fundamentals on multi-beam detection (1)

- **The received signal**
  - **The received signal at the input of the baseband multi-beam detector is given as follows,**

$$\underline{Y} = H\,\underline{X} + \underline{n}$$

$$\underline{Y} \in C^{Kx1}$$

Received samples

$$H \in \Re^{KxK}$$

Channel matrix

$$\left[h_{ij}\right] = \sqrt{G_i\left(\theta_{ij}\right)}$$

Channel coefficient

$$\underline{X} \in C^{Kx1}$$

Complex information symbol vector (*M*-ary PSK or QAM symbols)

$$\underline{n} \in C^{Kx1}$$

Noise sample vector

Fundamentals on multi-beam detection (2)

- **The basic detection criteria**
  - **Single-user matched filter receiver:**

$$\underline{\hat{X}} = \mathrm{mod}^{-1}\left(\underline{Y}\right)$$

  - **Multi-user linear receiver**

$$\underline{\hat{X}} = \mathrm{mod}^{-1}\left(R\underline{Y}\right)$$

$$R = H^{-1}$$

Decorrelating receiver

$$R = \left[H + \frac{1}{2}E\left\{\underline{n}\underline{n}^{T}\right\}\right]^{-1}$$

MMSE receiver

  - **Multi-user Maximum-Likelihood (ML) optimum receiver**

$$\underline{\hat{X}} = \min_{\underline{X}\in S}\left\{\left\|\underline{Y} - H\,\underline{X}\right\|^{2}\right\}$$

Search space of cardinality: M^{K}

Evolutionary algorithms for ML multi-beam detection (1)

- **Motivations:**
  - **Maximum Likelihood multi-beam detection may exhibit <u>a prohibitive computational complexity</u>, depending on the cardinality of the search space *S*;**
  - **In case of K=6 and M=64, the search space cardinality would increase up to 64^6 possible solutions to be tested (around 68.7 billions);**
  - **It is clear that the ML would be unfeasible in such a case. Alternative near-optimum optimization algorithms should be studied;**
  - **Evolutionary algorithms (Genetic Algorithms, Particle Swarm Optimization) might be the solution to provide near-optimum ML multi-beam detection.**

Evolutionary algorithms for ML multi-beam detection (2)

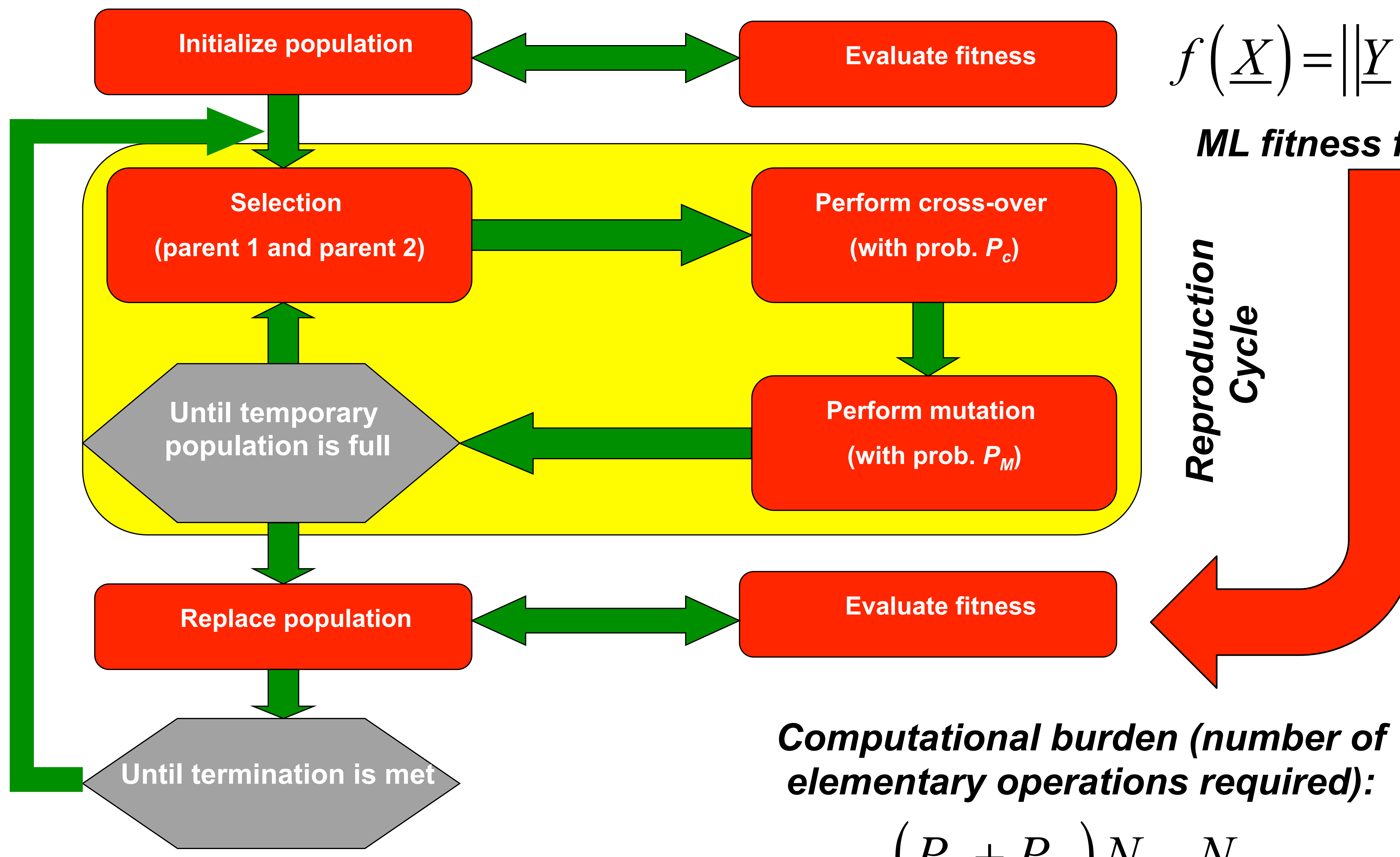
- **Genetic algorithms (GAs)**
  - **Genetic algorithms (known by the acronym GAs) are stochastic search methods inspired by the principles of natural selection and evolution;**
  - **We can say that the founding theory of GAs has been developed by the natural scientist Charles Spencer Darwin in his basic work[4];**
  - **GA optimizers are particularly effective when we need to find an approximate global maxima (or minima) in high-dimension, multi-modal function domain in a near-optimal manner.**

Evolutionary algorithms for ML multi-beam detection (3)

- **Genetic algorithms (GAs) – how they work[5]**
  - **Genetic algorithms process a fixed-cardinality set of potential solutions called population within a given number of iterations, called: generations;**
  - **The potential solutions forming the population are called individuals;**
  - **The population is initialized and then processed by stochastic operators, namely: selection, crossover and mutation. A probability is assigned to crossover and mutation operators.**
  - **Crossover and mutation produce new individuals on the basis of their suitability to survive that is established by the fitness function value.**

Evolutionary algorithms for ML multi-beam detection (4)

- **Genetic algorithms (GAs) – a functional diagram**



$$f\left(\underline{X}\right)=\left\|\underline{Y}-H\underline{X}\right\|^2$$

ML fitness function

Computational burden (number of elementary operations required):

$$\left(P_C+P_M\right)N_{pop}N_{gen}$$

Evolutionary algorithms for ML multi-beam detection (5)

- **Particle Swarm Optimization (PSO)**

  - **Like GAs, PSO starts from: populations of individuals (solutions) and fitness functions to evaluate populations;**

  - **<u>But</u> PSO is based on sociality and cooperation[6] instead of "natural (Darwinian) selection";**

  - **The distinguishing feature of PSO with respect to GAs is <u>the knowledge of the "individual neighborhood"</u>, thus configuring a social network of the individuals (called *particles*).**

Evolutionary algorithms for ML multi-beam detection (6)

- **Particle Swarm Optimization (PSO) – how it works**
  - **The typical PSO scenario is related to a group of birds that randomly search food in an area. There is only a piece of food in the area;**
  - **All the birds do not know where the food is. But they know how far the food is in each iteration. The most effective strategy to reach the food is to follow the bird, which is nearest to the food;**
  - **In PSO, each single particle is a ”bird” in the search space. All particles have their fitness values, derived by the fitness function to be optimized, and have velocities, which direct the flying of the particles.**

Evolutionary algorithms for ML multi-beam detection (7)

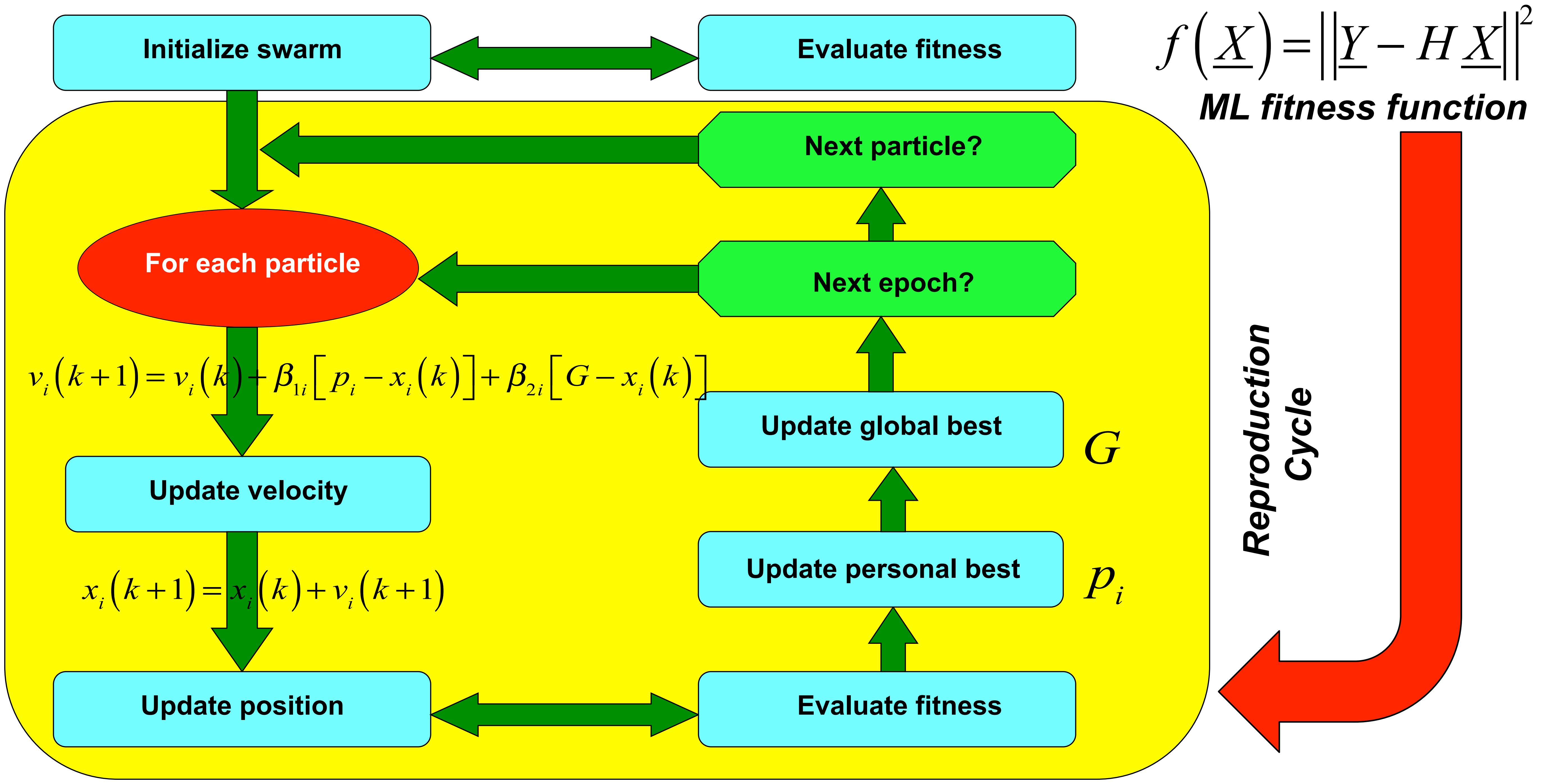
- **Particle Swarm Optimization (PSO) – concept of personal best and global best**
  - **The cooperative and social nature of PSO, opposed to the Darwinian "struggle of life" of GA, is highlighted by the concepts of personal best and global best;**
  - **At each iteration, the particle is updated by the best fitness value achieved so far (*personal best*) and by the best fitness value obtained so far by any particle in the population (*global best*);**
  - **On the basis of these two quantities, the particle updates its position and velocity.**

Evolutionary algorithms for ML multi-beam detection (8)

- **Particle Swarm Optimization (PSO) – a functional diagram**

Computational burden (number of elementary operations required):

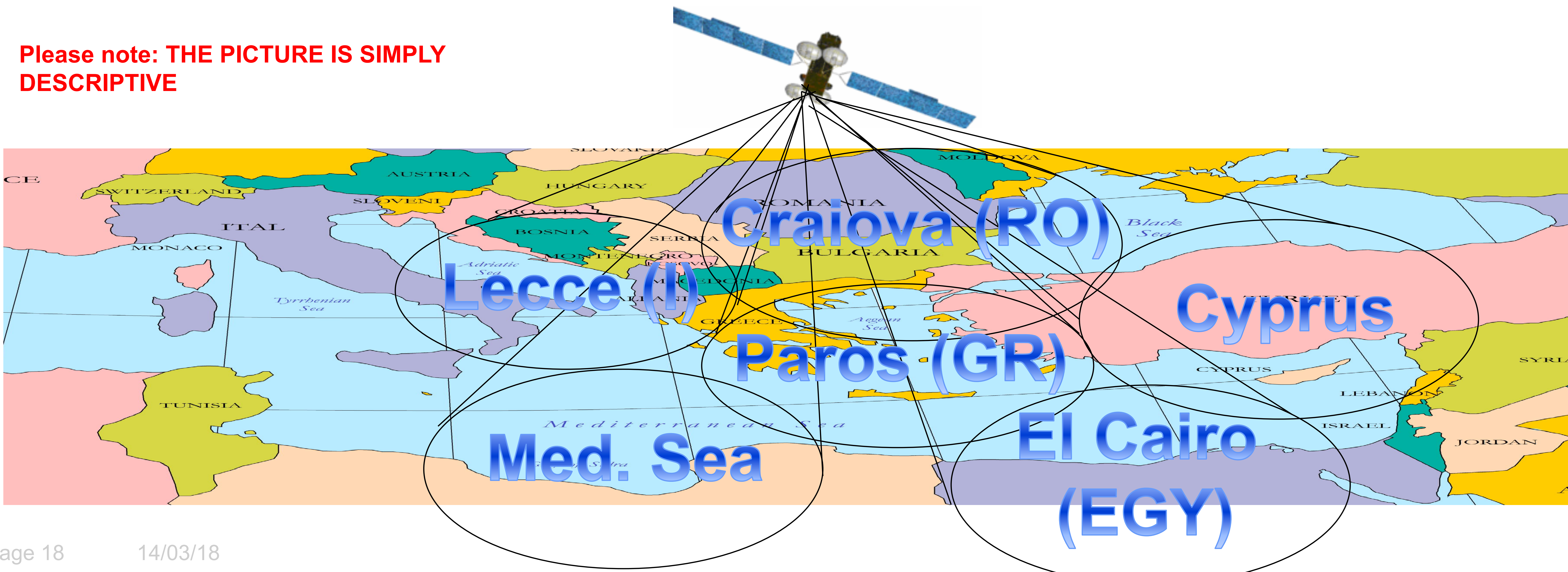
$$\frac{N_E S}{3}$$



Simulation results (1)

- **Simulation setup**
  - **Simulations have been performed in MATLAB environment;**
  - **A Ka-band multi-beam satellite system (f_c=20 GHz) with frequency reuse factor *K*=6 has been considered (Eutelsat KA-SAT). The adjacent beam angles have been computed by considering the following spot positions:**

Please note: THE PICTURE IS SIMPLY DESCRIPTIVE



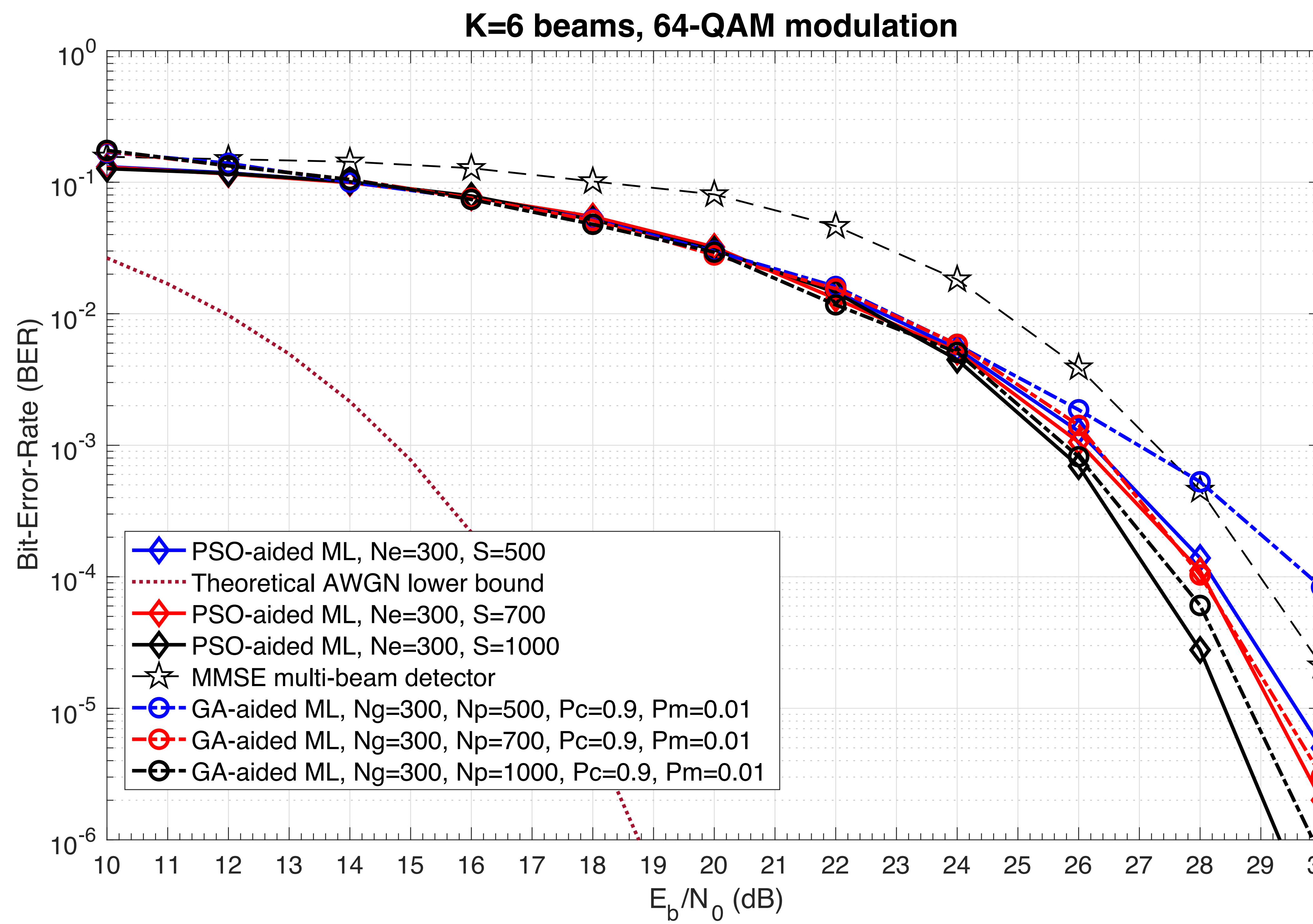
Simulation results (2)

- **Simulation results**
  - **With *K*=6 adjacent interfering beams, we consider 64-QAM modulation (optimum ML is computationally unaffordable). BER results are given as follows:**

COMMENT:

<u>Both GA and PSO outperform MMSE linear detection</u>, provided that iteration number and population size are properly set (PSO looks better performing and faster converging);

This proves that evolutionary detection strategies <u>are near optimum</u> also when the search space of ML is enormous and cannot be fully explored.



Conclusion and future work

- **Maximum-likelihood (ML) multi-beam detection is not realistic and, in many cases, computationally unfeasible;**
- **Evolutionary algorithms (GA and PSO) allow to provide effective near-optimum detection even when ML detection is computationally unaffordable;**
- **Future work should deal with a more formal and detailed analysis of the convergence of the proposed evolutionary approaches in the considered application framework.**

Essential bibliography

[1] C. Stallo and C. Sacchi, “Link performance analysis of multi-user detection techniques for w-band multi-beam satellites*,” in 2016 IEEE Aerospace Conference*, March 2016, pp. 1–9.

[2] R. Collin, *Antennas and radiowave propagation*, McGraw-Hill series in electrical and computer engineering. McGraw-Hill Higher Education, 1985.

[3] W. Zheng, B. Li, S. Ren, J. Chen, and J. Wu, “Interference modeling and analysis for inclined projective multiple beams of geo satellite communication systems,” vol. 756-759, 05 2014.

[4] C.S. Darwin: *“The Origin of Species by Means of Natural Selection”*, Murray: London, 1859.

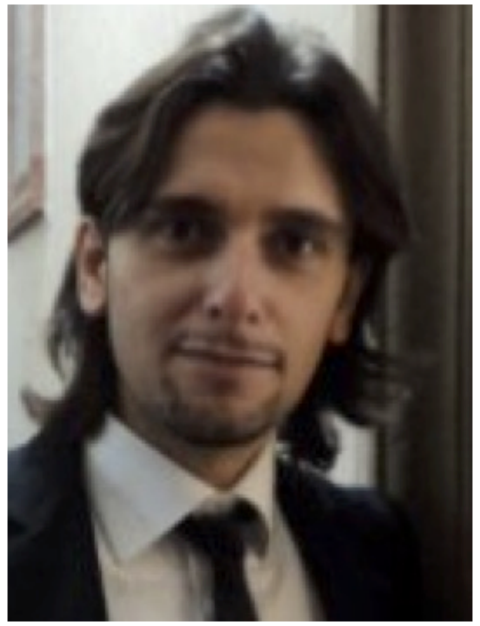
[5] D.E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley, Reading, MA: 1999.

[6] R. Eberhart and J. Kennedy, “A new optimizer using particle swarm theory,” in Micro Machine and Human Science, *1995. MHS ’95., Proceedings of the Sixth International Symposium on, Oct 1995*, pp. 39–43.

Contact information

For questions about this presentation, please send an e-mail to:

claudio.sacchi@unitn.it



cosimo.stallo@uniroma2.it

THANKS A LOT FOR YOUR ATTENTION!!
HAVE A NICE DAY IN BIG SKY!!