

# Towards a resolution of the firing squad problem with 5 states by metaheuristics

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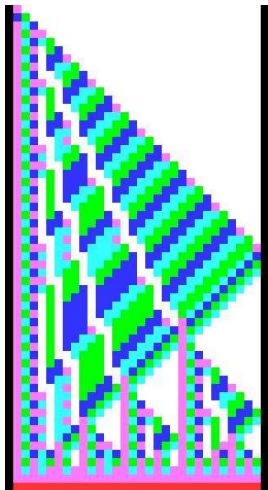
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# Outline

- 1 Introduction and motivations
- 2 To solve the problem
- 3 Experimental results
- 4 Conclusion and perspectives

## Firing squad problem (J.Myhill 1957)



- one firing man = one cell
- line of length  $n$  of firing squad
- Initial configuration :
  - the left cell in "general" state
  - right cells in "quiescent" state
- Exchange information between neighbors firing men = local transition function
- Goal : find a transition function such that  
 $\forall n$ , the final configuration is a line of cells in "firing" state.

## Previous works

Transition function which solve FSP in optimal time ( $2n - 2$  iterations) :

- E. Goto [1962] with thousand of states
- Waksman [1966] with 16 states
- Balzer [1967] with 8 states
- Mazoyer [1987] with 6 states

No transition function with 4 states (Balzer)

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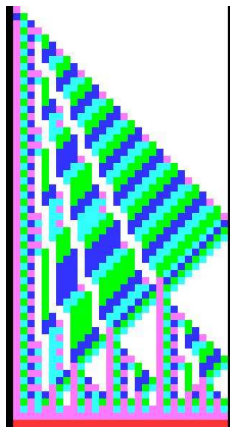
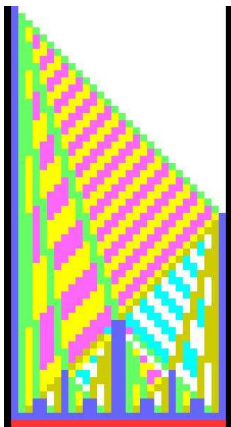
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Open Problem :

Does it exist transition which solve FSP with 5 states ?

# Space-time diagram at Balzer rules at 8 états (left) and of Mazoyer at 6 states (right)



## Goal of the work

- Goal : solve the firing squad problem (FSP) at 5 states

New approach to try for solving FSP :

- Definition of a family of optimization problems such that :  
Solving the family give a solution of FSP
- Solving the optimization problems (large and unknow search space) by the mean of stochatics optimization : metaheuristics

## Motivations of this work

- Enrico Formenti : “je connais un problème que tu pourrais essayer avec tes trucs”
- Previous works on Majority problem (find transition which classify the configuration according to density) :
  - analyze of the search space
  - design a new optimization algorithm
- objectif function is “black box” :  
no derivation, no analytic expression of the function
- Design new stochastic algorithms for hard optimization (NP-complet or more)
- example of automatic programmation of parallel machines



# Methodology

Goal : solve the firing squad problem at 5 states by the mean of stochastic optimization

1. Define two optimization problems :
  - $MAXF_n$  : for cell's line of length  $n$ , optimization fonction is the **number of synchronised cells** in “firing” state
  - $MAXF_{2,n}$  : optimization fonction is the **sum** of the number of synchronised cells in “firing” state for all line which the length is **between 2 and  $n$**
- Solving  $\forall n \geq 2, MAXF_{2,n}$  to solve the firing squad problem
2. Use and design metaheuristics to solve the optimisation problems

# Finite linear cellular automata (fICA)

$$\mathcal{A} = (\mathcal{Q}, \delta)$$

- $\mathcal{Q}$  finite set of states
- $q_l, q_i, q_f \in \mathcal{Q}$
- $\delta$  local transition function
- $\delta : \mathcal{Q} \cup q_b \times \mathcal{Q} \times \mathcal{Q} \cup q_b \rightarrow \mathcal{Q}$
- $\delta(q_b, q_l, q_l) = \delta(q_l, q_l, q_l) = \delta(q_l, q_l, q_b) = q_l$

Configurations :

- initial :  $C_0(1) = q_i$  and  $\forall j \in ]1, n], C_0(j) = q_l$
- final :  $\forall i \in [1, n], C_s(i) = q_f$

# Optimisation problem

## Definition

$$\mathcal{P} = (\mathcal{S}, f)$$

- $\mathcal{S}$  : set of potential solutions, search space
- $f : \mathcal{S} \rightarrow \mathbb{R}$  : objective function to maximize (or minimize)

Goal : find the set  $\mathcal{S}_{opt}$  such that

$$\forall s_{opt} \in \mathcal{S}_{opt}, \forall s \in \mathcal{S}, f(s) \leq f(s_{opt})$$

...or find solutions which is enough good for the “user” of the problem

In the firing squad problem,  
a solution = a transition function (set of rules)

# Metaheuristics

**Heuristic** : solving algorithm based on the "experience" which not necessary give an optimal solution

but I'd like :

- the most often as possible, a solution near optimal solutions
- the less often, a bad solution
- with low complexity
- simple to compute (in light version...)

# Metaheuristics

**Heuristic** : solving algorithm based on the "experience" which not necessary give an optimal solution

but I'd like :

- the most often as possible, a solution near optimal solutions
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**Metaheuristic** : set of heuristic defined by

- parameters which describe the set of heuristics
- a description of the heuristic in general term

## Metaheuristics classification

Stochastic algorithms with **unique** solution :

- (Random search),
- Ascent Algorithms : Hill-Climber (HC), first-ascent
- Simulated Annealing (Kirkpatrick *et al* 1983)
- Tabu search (Glover 1986)

Stochastic algorithms with **population** of solutions :

- Genetic algorithms (Holland 1975 and even before) : binary strings
- Evolution strategies (Schwefel 1970) : real optimization
- Genetic programming (Koza 92) : "program"
- Evolutionary Algorithm : the oecumenic algorithm
- Ant optimization (Bonabeau 1999) : route on graph
- memetic algorithms : combined local search with population

## Stochastic algorithms with unique solution

3 parts of local search algorithms :

- $\mathcal{S}$  set of solutions (search space),
- $f : \mathcal{S} \rightarrow \mathbb{R}$  objective function
- $\mathcal{V}(s)$  neighborhood, set of neighbor solutions of  $s$

*Generic algorithm*

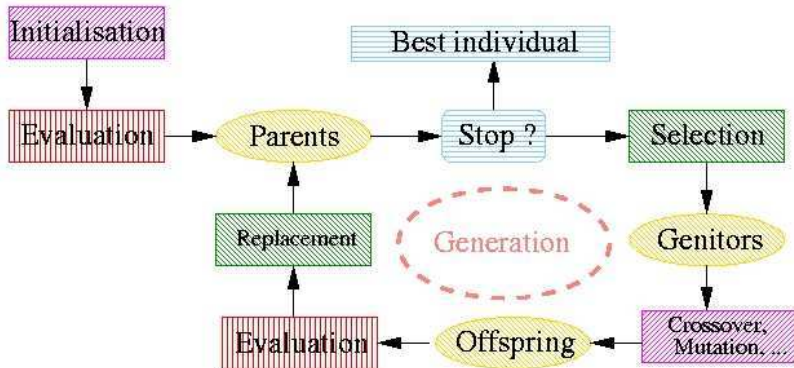
Choose initial solution  $s \in \mathcal{S}$   
**repeat**  
    choose  $s' \in \mathcal{V}(s)$   
     $s \leftarrow s'$   
**until** stop criterium verify

# Ascent algorithms


Hill-Climbing	First-Ascent
<p>Choose randomly initial solution <math>s \in \mathcal{S}</math></p> <p><b>repeat</b></p> <p style="padding-left: 2em;">Choose <math>s' \in \mathcal{V}(s)</math> such as <math>f(s')</math> is maximal</p> <p style="padding-left: 2em;"><math>s \leftarrow s'</math></p> <p><b>until</b> <math>s</math> local optimum</p>	<p><math>\text{step} \leftarrow 0</math></p> <p>Choose randomly initial solution <math>s \in \mathcal{S}</math></p> <p><b>repeat</b></p> <p style="padding-left: 2em;">choose randomly <math>s' \in \mathcal{V}(s)</math></p> <p style="padding-left: 2em;"><b>if</b> <math>f(s) \leq f(s')</math> <b>then</b></p> <p style="padding-left: 4em;"><math>s \leftarrow s'</math></p> <p style="padding-left: 2em;"><b>end if</b></p> <p style="padding-left: 2em;"><math>\text{step} \leftarrow \text{step} + 1</math></p> <p><b>until</b> <math>\text{stepMax} \leq \text{step}</math></p>



# Generic Evolutionary Algorithm



 Stochastic operators: Representation dependent

 "Darwinism" (stochastic or determinist)

# Memetic algorithms

Combined :

- efficient local search (local operator)
- population search based (global operator)

⇒ initialisation of the population use local search

⇒ mutation operator is replaced by local search

Avantages :

- at least, the same performance as efficient local search !
- better compromise between exploration/exploitation

## MAXF<sub>n</sub> and MAXF<sub>2,n</sub> families of problems

- Optimization problem MAXF<sub>n</sub> :

$$f_n : \mathcal{S} \rightarrow [0, n]$$

$$f_n(s) = \begin{cases} 0 & \text{if } \forall t \leq T_{max}, \omega(C_t) = 0 \\ \omega(C_t) & \text{if } \exists t \leq T_{max}, \forall t' < t, \omega(C_{t'}) = 0 \end{cases}$$

$T_{max}$  is the limit time before synchronisation

$\omega$  counts the number of firing state in the configuration  $C_t$

$$\omega(C_t) = \sum_{i=1}^n \xi_{C_t(i)}^{q_f}$$

- Optimization problem MAXF<sub>2,n</sub> :

$$f_{2,n} : \mathcal{S} \rightarrow [0, \frac{n(n+1)}{2} - 1]$$

$$f_{2,n}(s) = \sum_{i=2}^n f_i(s)$$

## Search space

$\mathcal{S} = \{ \delta \mid (Q, \delta) \text{ IfAC}, \#Q = 5 \}$ , but rules with "firing" state are not use

Neighborhood of  $s$  : solutions with one rule changed

- Whole search space :
  - number of rules :  $4^3 - 1$  "central" rules,  $4^2 - 1$  rules for left and right bounds  
So, 93 rules
  - size of search space : 5 possible states for each rule  
 $5^{93} \approx 10^{66}$
  - size of neighborhood : 4 other possible states for each rule  
 $93 \times 4 = 372$

## Search space : Restricted search space

$\mathcal{S} = \{ \delta \mid (Q, \delta) \text{ IfAC}, \#Q = 5 \}$ , but rules with "firing" state are not use

Neighborhood of  $s$  : solutions with one rule changed

- Only "firing" state for the rules  $333 \rightarrow q_f$  and  $33 \rightarrow q_f$ 
  - number of rules : 90 rules
  - size of search space : 4 possible states for each rule  
 $4^{90} \approx 10^{54}$
  - size of neighborhood : 3 other possible states for each rule  
 $90 \times 4 = 270$

## Search space : Restricted search space

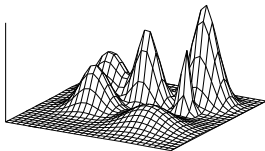
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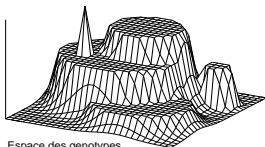
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In which search space is it easier to find good solutions?

# Fitness landscape



Fitness



Espace des genotypes

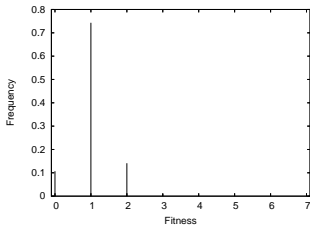
*Fitness landscape*  $(\mathcal{S}, \mathcal{V}, f)$  :

- $\mathcal{S}$  : set of potential solutions,
- $\mathcal{V} : \mathcal{S} \rightarrow 2^{\mathcal{S}}$  : neighborhood relation,
- $f : \mathcal{S} \rightarrow \mathbb{R}$  : objective function.

## Fitness landscape

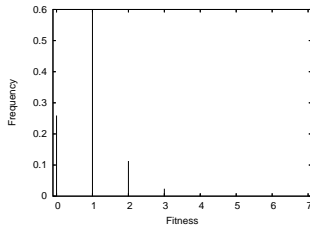
Frequency of the value of objective function for random solutions

Whole search space



average 1.0522  
maximum 5

Restricted search space



average 0.9264  
maximum 7

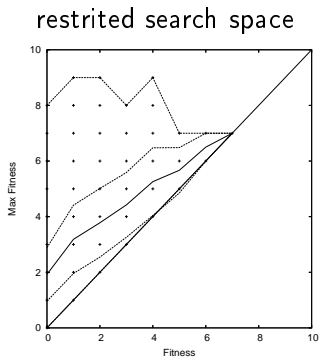
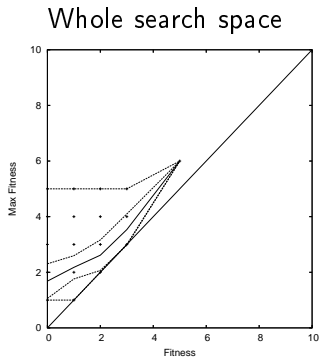
- Average is lower for Restricted SS (more 0 fitness value)
- The tail is higher for restricted SS

⇒ Restricted seems "easier"



## Fitness landscape

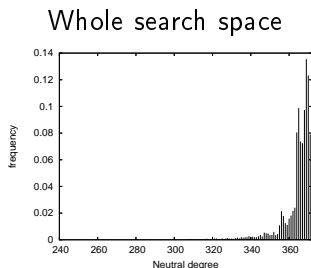
Correlation between high fitness value in the neighborhood with fitness value of solutions



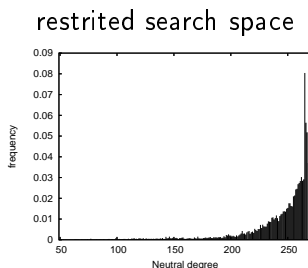
⇒ Restricted seems "easier"

# Fitness landscape

Number of equal fitness value in the neighborhood (Neutrality)



$363.926 \approx 97.8\%$



$243.865 \approx 90\%$

⇒ Restricted seems "easier"

## Results on MAXF<sub>101</sub>

Metaheuristic	<i>mean</i> <sub><i>std.dev.</i></sub>	Max.
HC	3.7871 <sub>1.9767</sub>	18
First-Ascent	13.735 <sub>2.73067</sub>	25
AE	6.2471 <sub>1.03071</sub>	11

## Results of memetic algorithm on MAXF<sub>101</sub>

	Local search rate				
	0.1	0.5	0.8	0.9	1.0
0.0	13.8 <sub>2.1</sub> 18	15.9 <sub>3.4</sub> 27	16.5 <sub>2.6</sub> 25	16.3 <sub>2.6</sub> 23	16.3 <sub>2.4</sub> 23
0.3	13.7 <sub>2.7</sub> 20	16.3 <sub>2.7</sub> 25	15.9 <sub>2.1</sub> 20	16.7 <sub>2.3</sub> 22	17.8 <sub>3.1</sub> 26
0.5	14.3 <sub>2.6</sub> 21	17.2 <sub>3.7</sub> 29	16.7 <sub>2.0</sub> 20	17.6 <sub>2.3</sub> 22	17.0 <sub>2.6</sub> 22
0.8	15.2 <sub>2.7</sub> 22	16.2 <sub>2.4</sub> 22	17.5 <sub>2.6</sub> 23	17.5 <sub>2.2</sub> 23	17.4 <sub>2.8</sub> 26
1.0	14.2 <sub>1.7</sub> 17	16.5 <sub>2.4</sub> 21	17.1 <sub>2.3</sub> 24	16.6 <sub>2.4</sub> 25	16.6 <sub>2.7</sub> 25

# Space-time diagram of best transition function on $\text{MAXF}_{101}$

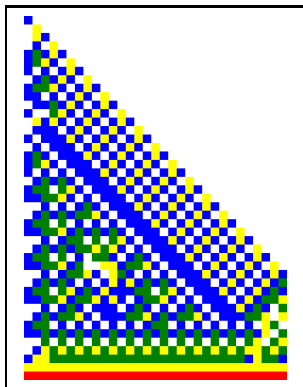


31 cells synchronized in firing state

## Solved problems of $\text{MAXF}_n$

Metaheuristic	Solved length $n$
Hill-Climbing	2, 3, 4, ..., 20
First-Ascent	2, 3, 4, ..., 29
memetic-FA	2, 3, 4, ..., 31

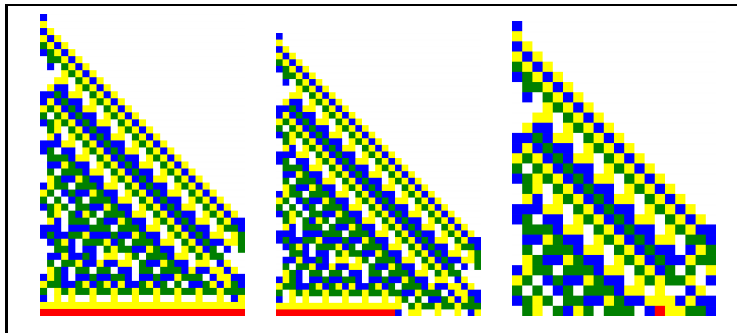
# Space-time diagram of trans. func. which solve $\text{MAXF}_{31}$



31 men which open fire in the same time!

# Space-time diagram of the same solution for different lengths

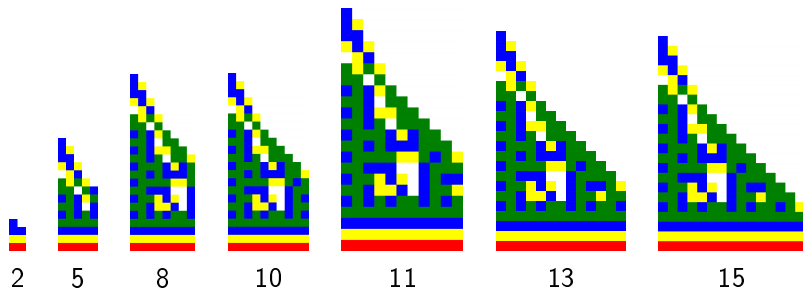
But only a specific length is solved.





## Results on $\text{MAXF}_{2,n}$

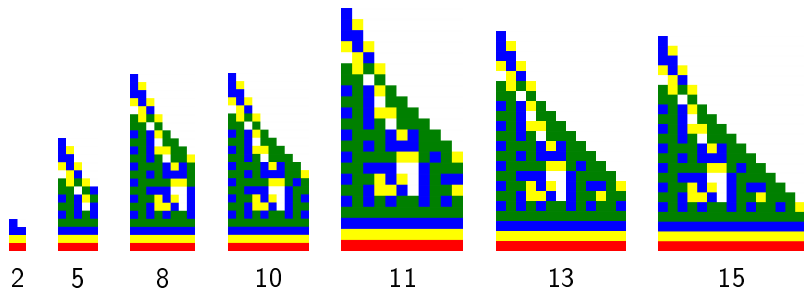
memetic-FA : Solve  $\forall n \in \{2, 3, 4, \dots, 15\}$



Space-time diagram for a solution for the length 15

## Results on $\text{MAXF}_{2,n}$

memetic-FA : Solve  $\forall n \in \{2, 3, 4, \dots, 15\}$



Space-time diagram for a solution for the length 15

...do not synchronize 16 cells

## Comparison with the result of Balzer

With 4 states :

- Balzer program shows the non existence of a transition function
- Find transition function which synchronise  $\forall n \in \{2, \dots, 8\}$ , but not  $\forall n \in \{2, \dots, 8, 9\}$

With 5 states

- $\exists$  transition function which synchronise  $\forall n \in \{2, \dots, 15\}$
- So, for the same prove, we must show for length  $> 15$

## Conclusion

- our approach : stochastic optimization based on local search and population (metaheuristics)
- define families of optimization problems
- transition functions is specific for cells line of length  $\leq 31$
- Find some transition functions which synchronise line which has a length between 2 and 15
- FSP is very hard optimization problem ... still an open question

## Perspectives

- Explain the space-time diagram of the transition functions (signals,...) to design more efficient algorithms
- Define new objective function (take care of the synchronising time,...)
- Define some middle stages
- Uses some other metaheuristic (simulated annealing, tabu search,...)
- Design a efficient recombinaison between solutions (based on frequency of use of rules,...)
- Study the search space
- Study the search spaceS

# Define new objective function

