Intelligent Modeling of Sugar-cane Maturation

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Agenda

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III. AI: Artificial Neural Networks
IV. AI: Genetic Algorithms
V. Modeling Sugarcane Maturation
VI. Computer tool, Simulation and Results
VII. Conclusion & Future Works

Part I

Motivation

Introduction

- Sugarcane has 37 different species (not to mention the hybrids)
- Each species has its own agronomical behavior along the year
- Several factors interfere with sugarcane maturation
- Modeling maturation curves of each species can have a profound economical impact
- Artificial intelligence techniques can be used to model maturation of sugarcane [Lima Neto, 1997] [Trigo, 2005]

Objectives of this work

1) To conceive an intelligent computer tool that models sugarcane maturation curves

2) To devise an automatic calibration means for the computer tool produced to model sugarcane maturation curves

Part II

Artificial Intelligence

Artificial Intelligence (in short)

A computer system (HW / SW) that is able to learn and store this knowledge to a further situation (that can also be a new one)

Conventional *vs.* Intelligent Systems

Conventional Systems	**Intelligent Systems**
-Trivial computations	+Human level-computation
-Pre-conceived solutions	+Taylor made outputs
-Not-able to generalize	+Able to generalize
-Non-adaptable	+Adaptable
+Deterministic (precise)	-Non-deterministic

AI myths about Intelligent Systems

1. They will replace decision makers	**Myth**
2. They will replace IT people	**Myth**
3. They are infallible	**Myth**
4. They demand special machines	**Myth**
5. They are slow	**Myth**
6. They are expensive	**Myth**
7. They need highly-qualified users	**Myth**
8. They need highly-qualified programmers	**+-Fact**

Part III

IA: Artificial Neural Networks

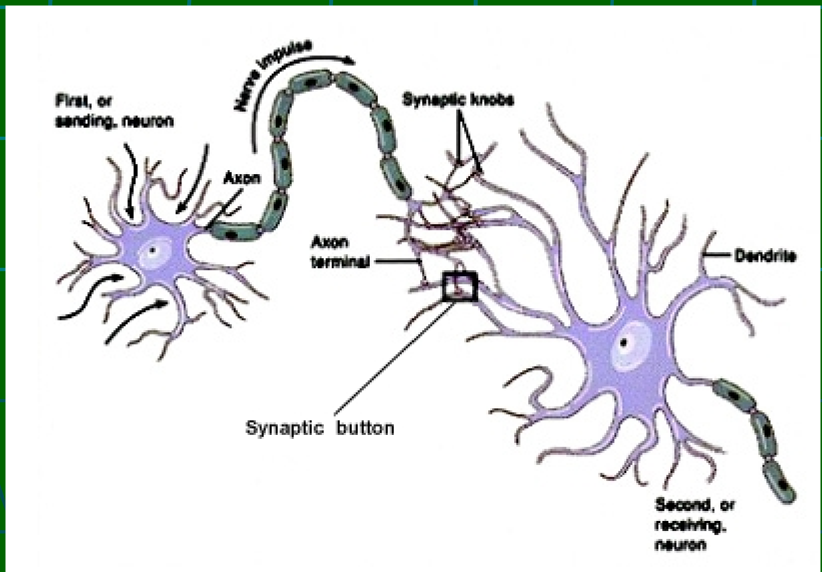
Artificial Neural Networks (in short)

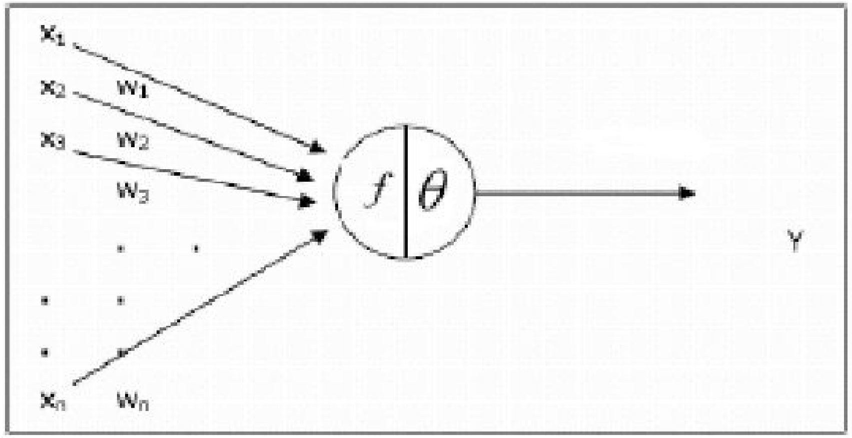
Artificial Neural Network is an AI technique inspired in the human brain organization. It incorporates the following principles:

- Processing is carried out in simple units – neurons
- Units are highly connected to each other – neural network
- Knowledge is stored in a distributed manner on weights of neural connections – synapses of axons;
- Learning happens thru repetition of training patterns – examples
- Knowledge is derived from hidden correlations among input-output variable – productivity factors and indicators

Natural *vs.* Artificial Networks

Natural x Artificial





Model of an artificial neuron

Activation function

$$Y = f\left(\left(\sum_{i=1}^{n} W_i \cdot X_i\right) - \theta\right)$$

Where:

- W_i – Synaptic weights
- X_i – Inputs presented to neuron
- θ – Bias / Threshold

Mean square error

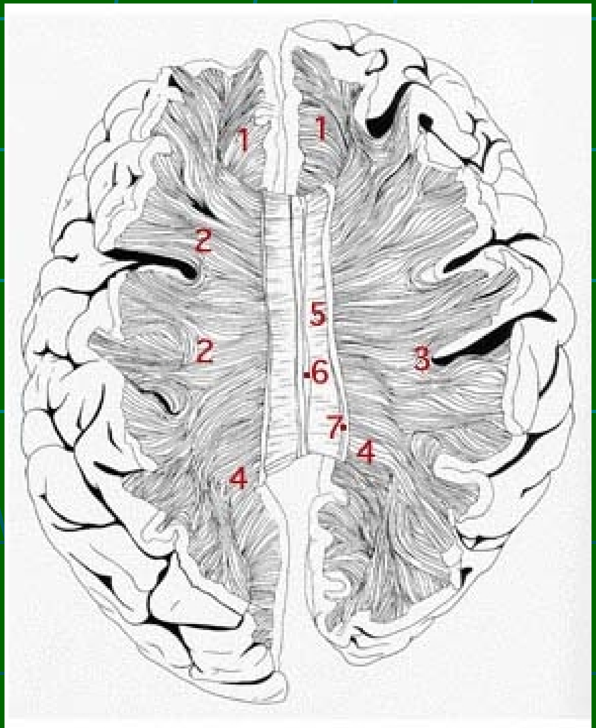
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(d_i - o_i)^2$$

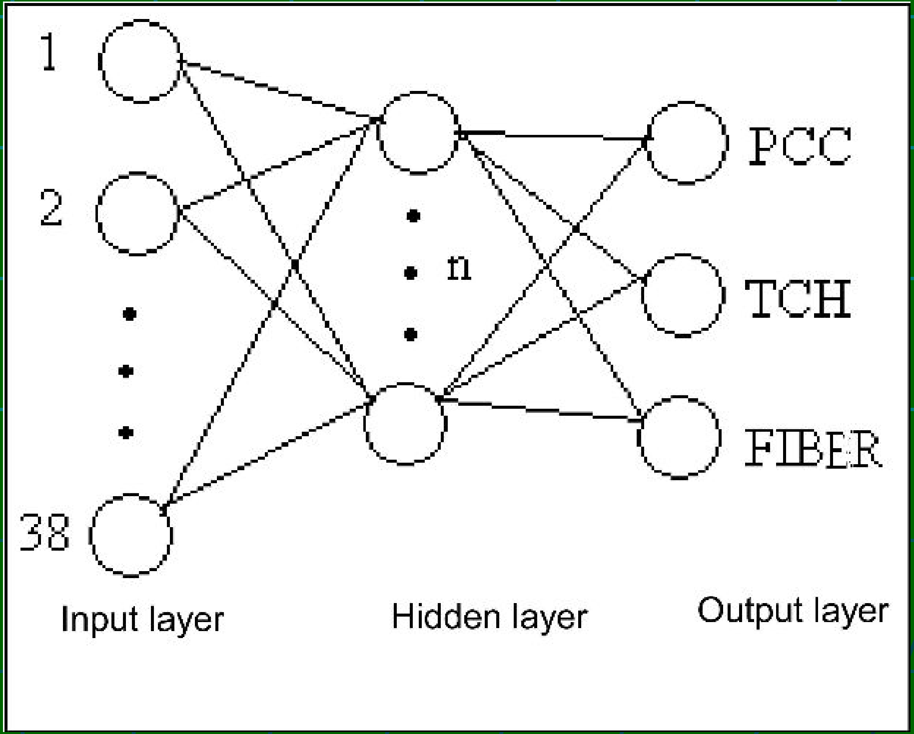
Where:

- d_i – Desired output
- o_i – Computed output

Natural *vs.* Artificial Networks

Natural x Artificial





Artificial Neural Networks - use

ANNs are able to model any mathematical function (e.g. sugarcane maturation curve)

Artificial Neural Networks - Problems

- Artificial Neural Networks produce excellent results in problems of optimization, classification and forecasting. However, there are a few inconveniences:
  1. Network layout has to be arranged ad-hoc
  2. Training data have to be gathered heuristically
  3. Training parameters have to be exhaustively experimented

ANN – Training parameters (#3)

- Not only parameters have to be exhaustively experimented, but due to huge number of combinations among them, this process is:

1. Slow
2. Tedious
3. Sometimes, ineffective

Part IV

IA: Genetic Algorithms

Genetic Algorithms (in short)

GA is an AI approach that is inspired in nature (evolution); that is, survival of the fittest

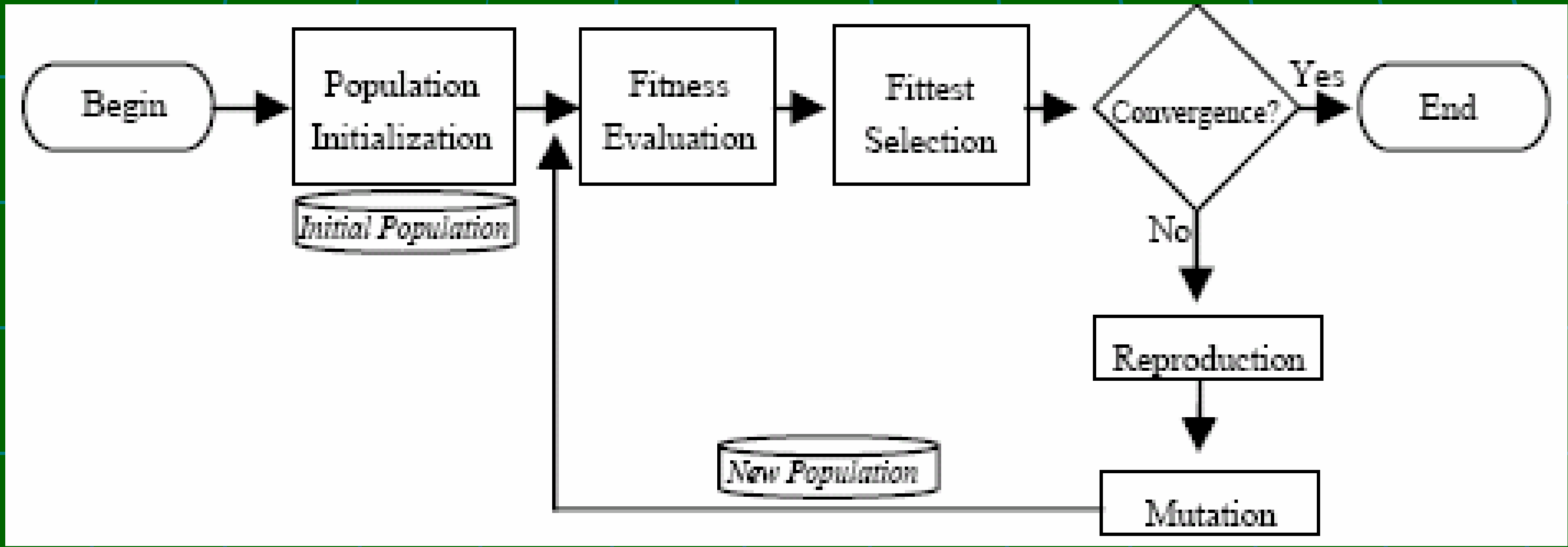
Genetic Algorithms

- They are computational search techniques
- Problem features are coded in “genes”
- Problem candidate solutions are chromosomes
- The best solution is found thru evolution within the population (maximization)
- Some parameters are: pop size, features to be coded, evolution steps, mutation etc

Genetic Algorithms - Use

GAs are ideal options to solve search problems (e.g. a suitable set of parameters for a given ANN)

Genetic Algorithms



Processing cycle for a simple GA

Part V

Modeling Sugarcane Maturation

Productivity factors

- There are many productivity factor, for example:

  -Cane variety (type);

  -Soil/Topology;

  -Climate;

  -Sowing date;

  -Age;

  etc

Productivity indicators

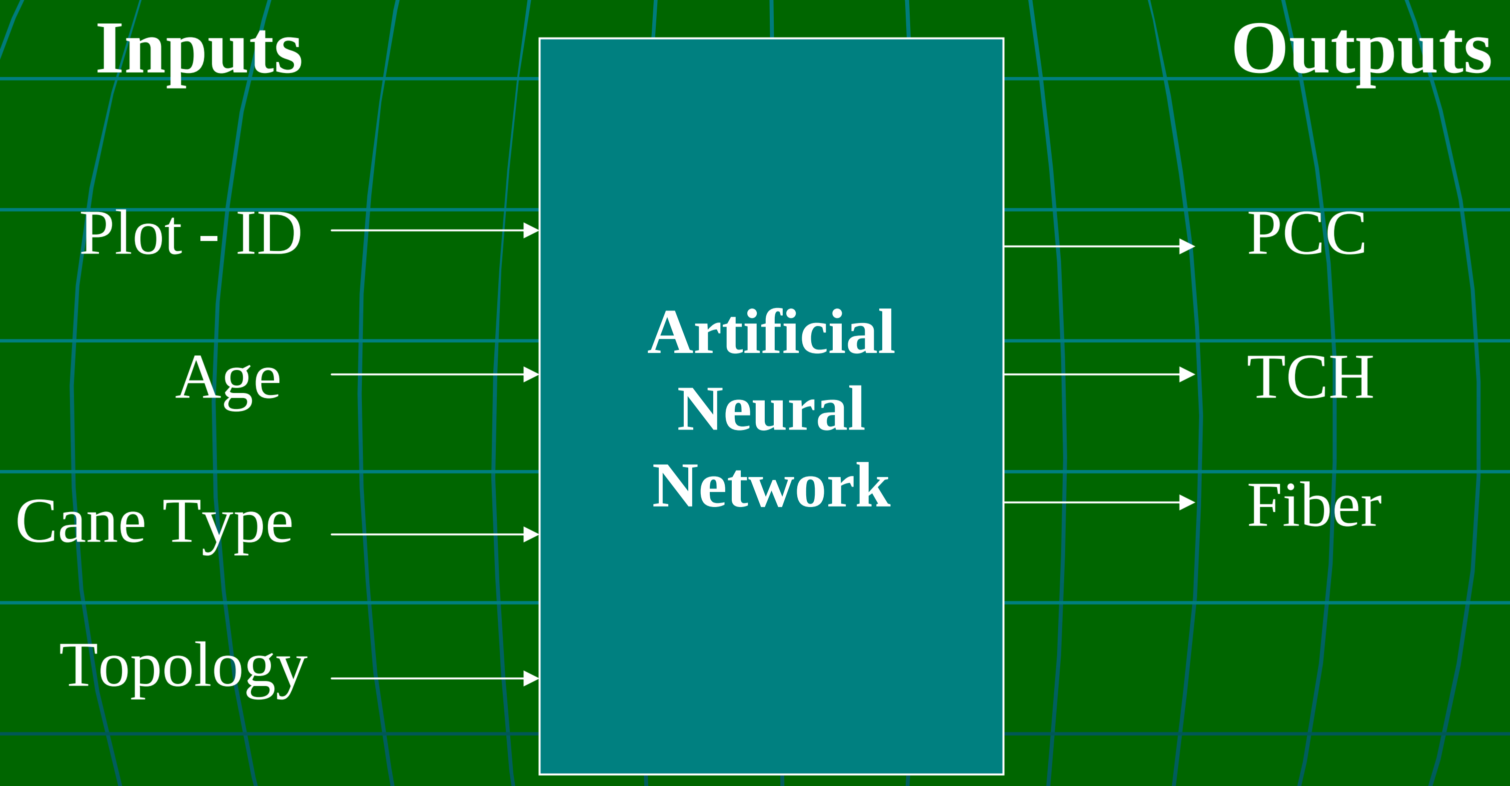
- There are many productivity indicators, for example:

-PCC (sucrose);

-TCH (biomass);

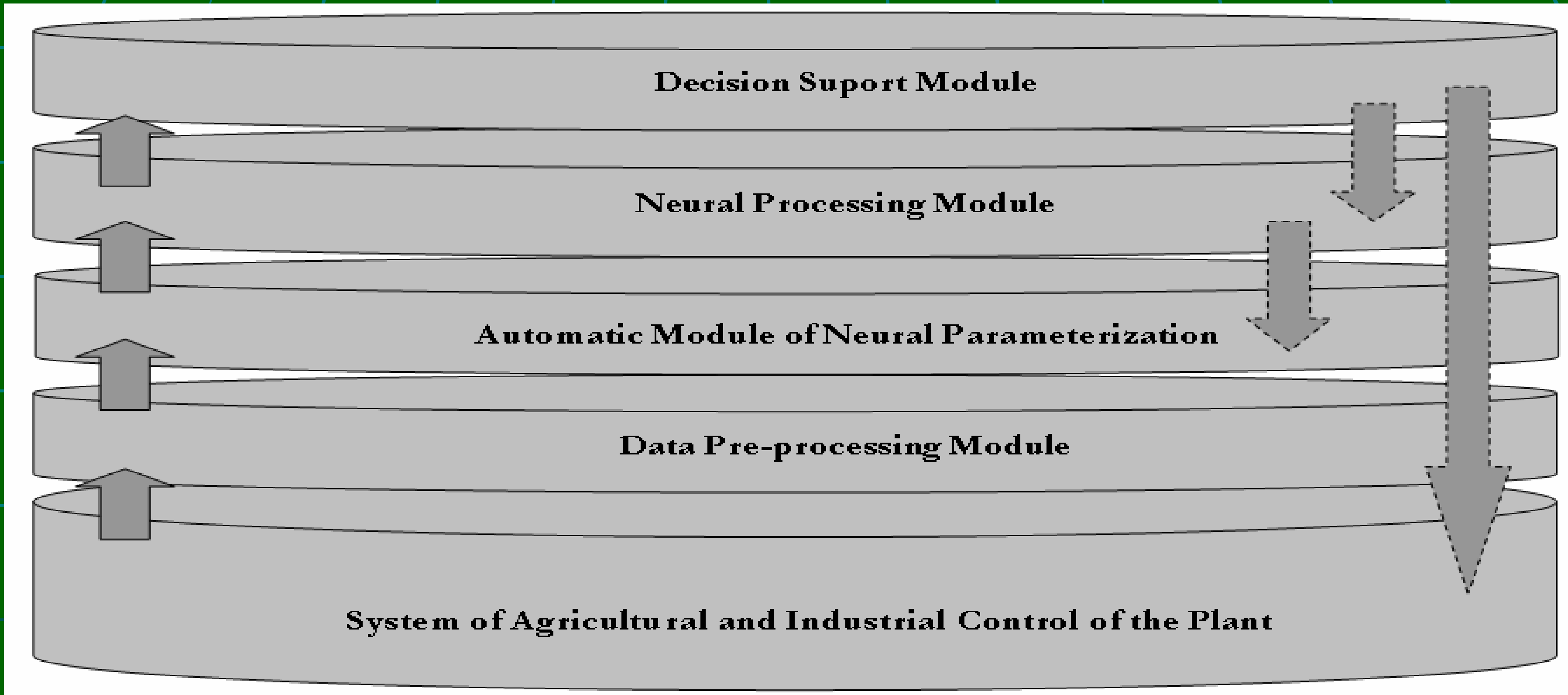
-Fiber (quality of).

Productivity factors and indicators



Schematic view of ANN used for forecasting in this work

Complete solution - overview



Part VI

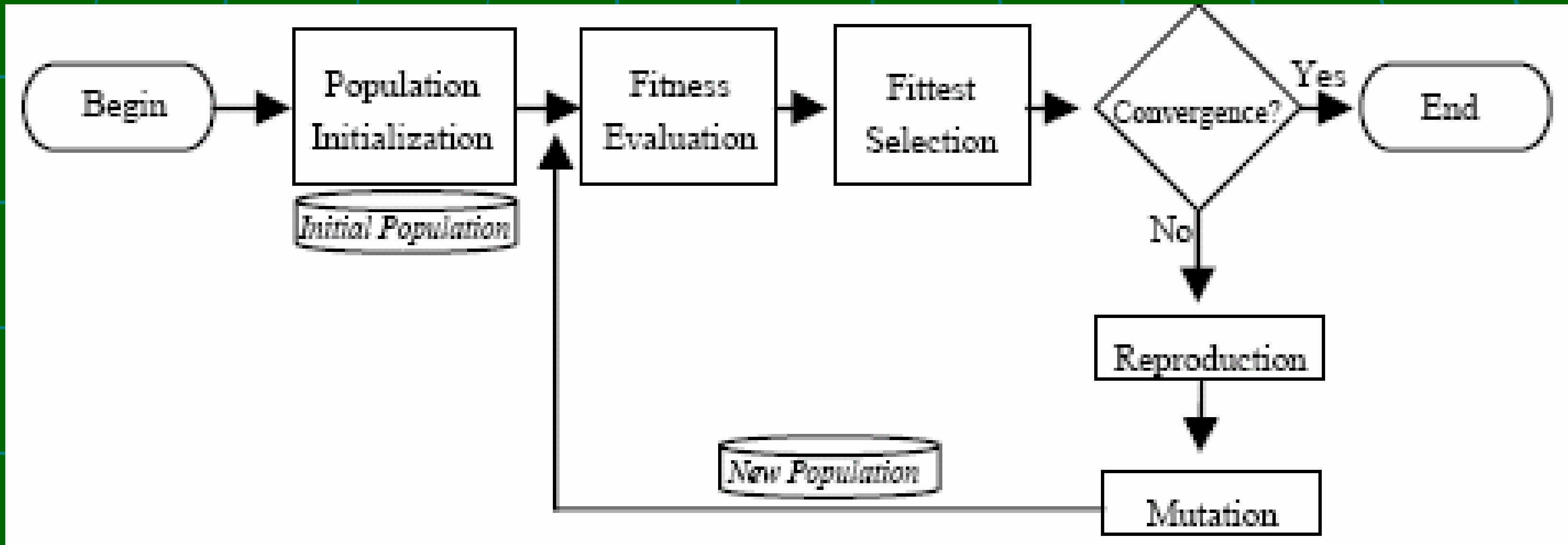
Computer tool, Simulation and Results

Coding ANN parameters as genes

- Binary coding of four ANN parameters
  - Neuron number of first layer – 5 bits (gene-1)
  - Neuron number of second layer – 5 bits (gene-2)
  - Activation function – 1 bit (Logistic or Tangent) (gene-3)
  - Learning rate – 7 bits (gene-4)
    - 5 initial bits to exponent (power of 2)
    - 2 remaining bits to first decimal figure
- Example
  - g1 = 7, g2 = 12, g3 = Tangent e g4 = 0 + 2^{-20}

0	0	1	1	1	0	1	1	0	0	1	0	0	1	1	0	0	0

Genetic Algorithms



Processing cycle for a simple GA

Algorithm – step 1

- Initial population

0	1	0	1	1	0	1	0	1	0	0	0	0	1	1	0	1	1
0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	0	0	1
1	1	0	1	0	1	0	0	1	0	1	1	0	0	1	0	1	0
0	0	0	1	1	0	1	0	1	0	1	0	1	1	0	0	1	0
1	0	1	1	0	0	1	0	1	1	0	0	0	1	1	0	0	1
0	1	0	0	0	1	1	0	1	0	0	1	0	1	0	0	1	1

Algorithm – step 2

- Neural engine evaluation (fitness evaluation)

0	1	0	1	1	0	1	0	1	0	0	0	0	1	1	0	1	1	134,2
0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	0	0	1	110,7
1	1	0	1	0	1	0	0	1	0	1	1	0	0	1	0	1	0	089,1
0	0	0	1	1	0	1	0	1	0	1	0	1	1	0	0	1	0	101,8
1	0	1	1	0	0	1	0	1	1	0	0	0	1	1	0	0	1	115,2
0	1	0	0	0	1	1	0	1	0	0	1	0	1	0	0	1	1	145,0

Algorithm – step 3

- Sorting out

0	1	0	0	0	1	1	0	1	0	0	1	0	1	0	0	1	1	145,0
0	1	0	1	1	0	1	0	1	0	0	0	0	1	1	0	1	1	134,2
1	0	1	1	0	0	1	0	1	1	0	0	0	1	1	0	0	1	115,2
0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	0	0	1	110,7
0	0	0	1	1	0	1	0	1	0	1	0	1	1	0	0	1	0	101,8
1	1	0	1	0	1	0	0	1	0	1	1	0	0	1	0	1	0	089,1

Algorithm – step 4

- Selection (1st e 2nd, 2nd e 3rd, 3rd e 4th)

0	1	0	0	0	1	1	0	1	0	0	1	0	1	0	0	1	1	145,0
0	1	0	1	1	0	1	0	1	0	0	0	0	1	1	0	1	1	134,2
1	0	1	1	0	0	1	0	1	1	0	0	0	1	1	0	0	1	115,2
0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	0	0	1	110,7
0	0	0	1	1	0	1	0	1	0	1	0	1	1	0	0	1	0	101,8
1	1	0	1	0	1	0	0	1	0	1	1	0	0	1	0	1	0	089,1

- Obs: 5th and 6th did not reproduce

Algorithm - 5

- Evolution: crossover 50 % and elitism

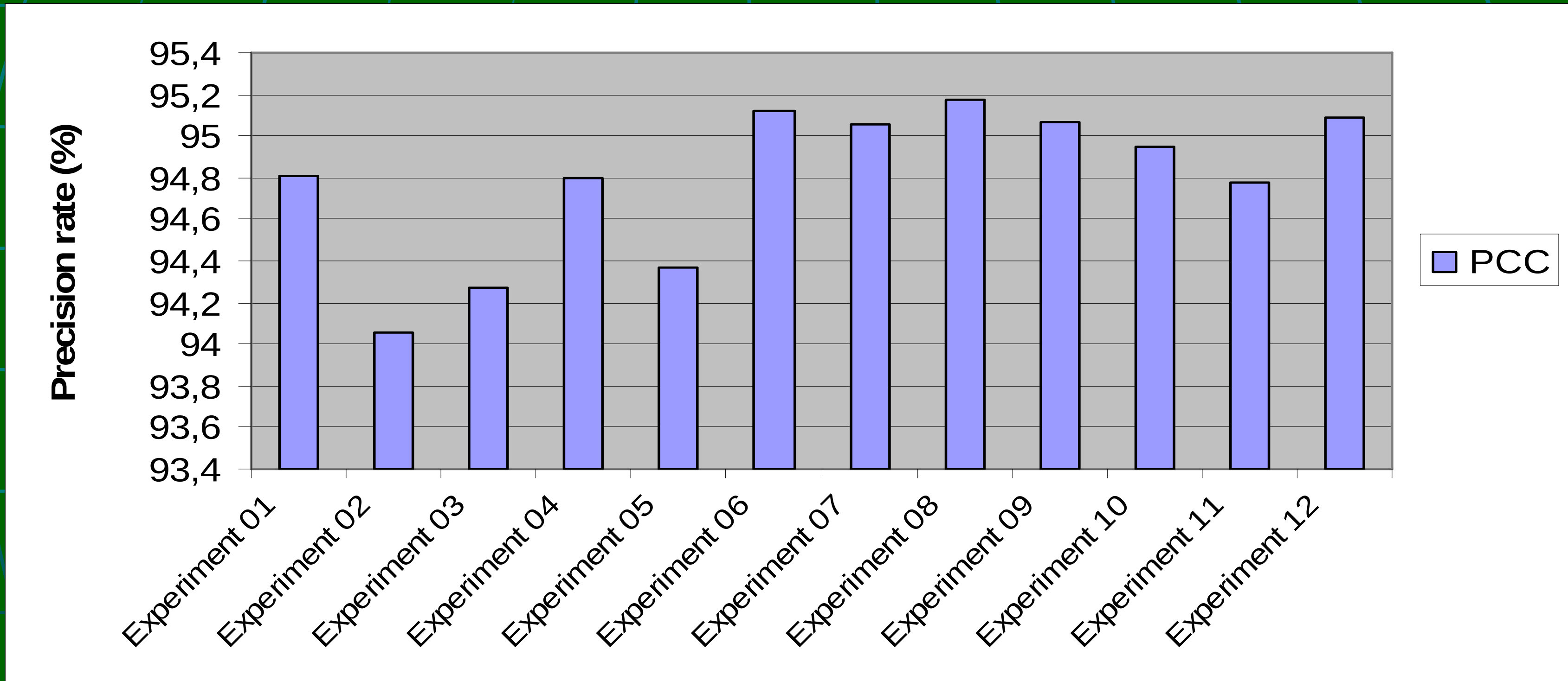
0	1	0	0	0	1	1	0	1	0	0	1	0	1	0	0	1	1
0	1	0	0	0	1	1	0	1	0	0	0	0	1	1	0	1	1
0	1	0	1	1	0	1	0	1	0	0	1	0	1	0	0	1	1

Experiment

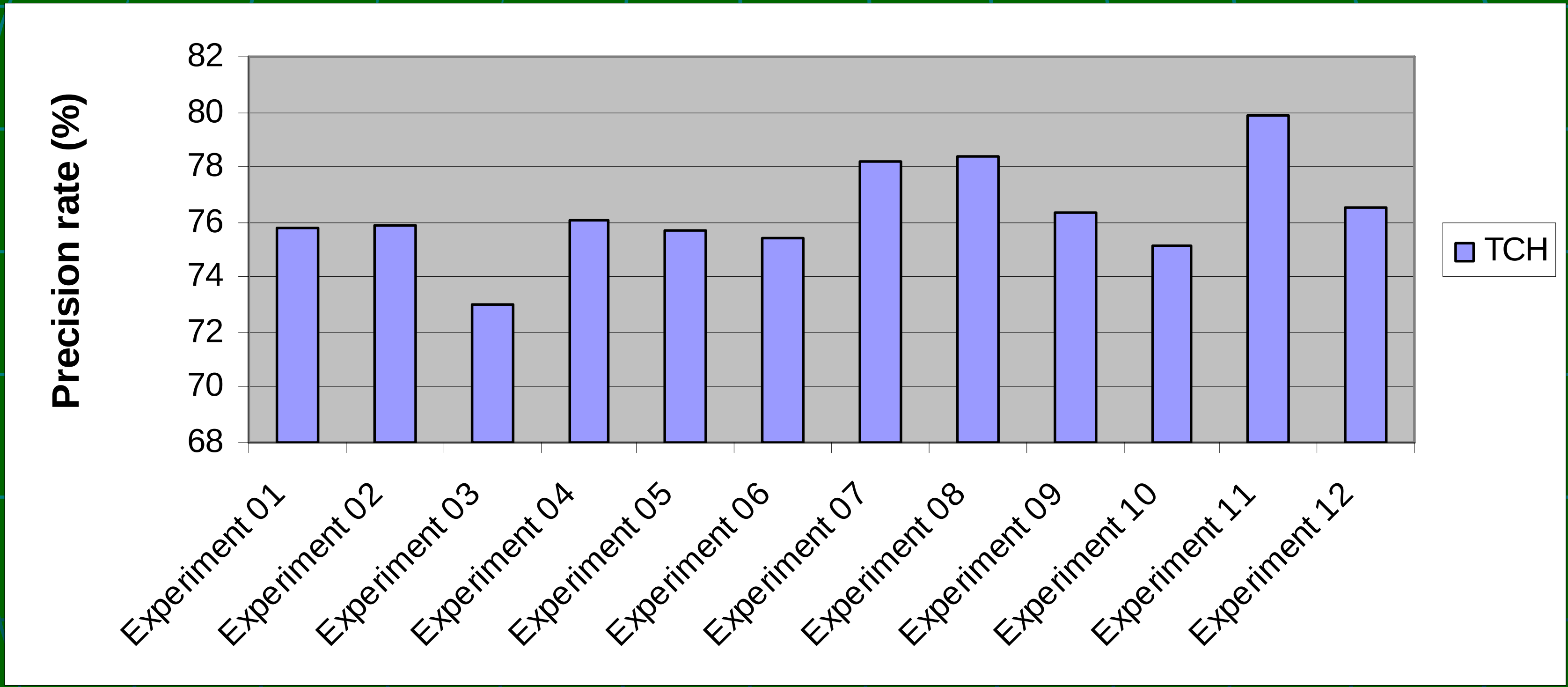
- #Neurons in hidden layer and learning rate?
- GA parameters: #generations and #individual

Experiments	Generation Number	Number of Individuals	Neurons per layer	Learning Rate
1	10	10	[06]	0.091
2	10	15	[12][06]	0.125
3	10	20	[10][01]	0.125
4	10	25	[03][03]	0.091
5	15	10	[05][01]	0.091
6	15	15	[06]	0.091
7	15	20	[04][01]	0.125
8	15	25	[04]	0.091
9	20	10	[06][08]	0.125
10	20	15	[08][04]	0.2
11	20	20	[05][01]	0.091
12	20	25	[08][10]	0.091

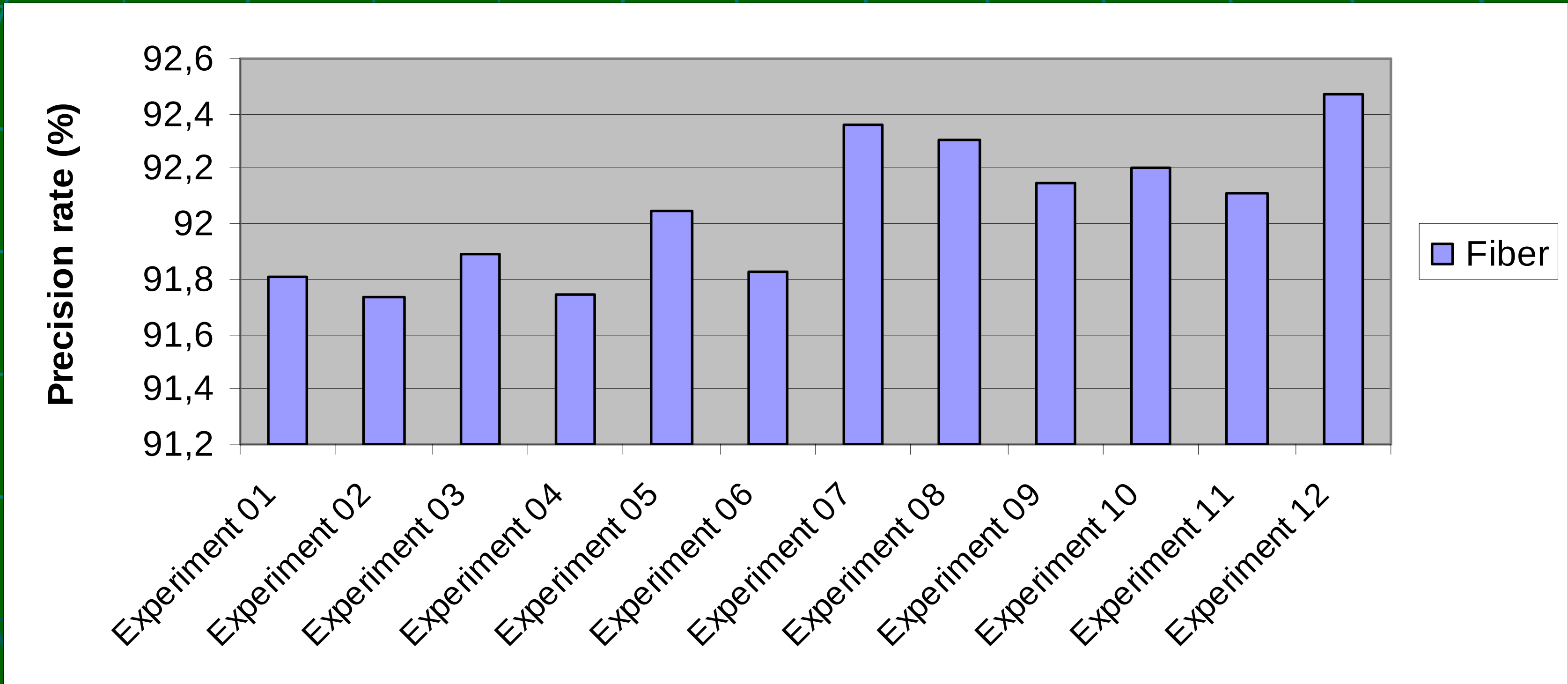
ANN automatically parameterized



ANN automatically parameterized



ANN automatically parameterized



Results

- Average performance of ANNs automatically parameterized when compared with manual
- At the same time, a marked reduction on the training cycles from 10000 (Pacheco, 2005) and 2795 (Trigo, 2005), to mere 2000 (this work).

Indicators	[Buarque, 1998] (%)	[Pacheco *et al*, 2005] (%)	[Trigo *et al*, 2005] (%)	This work–Exp # 11 (%)
PCC	95.330	95.620	95.401	94.777
TCH	49.200	78.070	79.475	79.910
Fiber	89.680	92.520	92.736	92.110
Average	78.070	88.737	89.204	88.932

Part VII

Conclusion & Future Works

Conclusions

- GA can automatically search and find reasonably good parameters for ANNs
- Automatically parameterized ANNs present forecast performance compatible with manually tuned ANNs
- We advocate the automatic process of searching ANN parameters as it speeds-up applications of output

Future work

- Improve GA parameter selection
- Use a more aggressive strategy of evolution
- Include other RNA parameters within the GA search

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Thank you !

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