Fuzzy Inferencing:
A Novel, Massively Parallel Approach [1]

Andrzej Buller [2]

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Abstract

The report presents a model of a fuzzy control in which decisions are worked out based on results of a competition between groups of agents which, represented by binary words, navigate in a neural working memory. Each agent is endowed with a strategy of its own behavior and carries its opinion. The opinions are symbolic statements encoding facts and/or rules. A Fuzzy Knowledge Base provides rules, as well as the values of membership of given measurements to appropriate facts interpreted as fuzzy sets. At a given moment an indoctrinating device generates a fact or its negation with a probability calculated based on related membership value. A debate in the Society of Agents results in a victory of adherents of a particular solution. An ultimate decision is based on a poll. A hardware facilitating this kind of computation, as well as some simulation results are discussed.

Key words: Fuzzy control, neural networks, distributed inferencing

1. Introduction

Massively parallel computation provides the opportunity of employing new paradigms in Artificial Intelligence [1]. Buller [2] notes that classic fuzzy calculus based on Łukasiewicz and Zadeh's set-theoretic [3] or other mathematical operations (see [4]) may be replaced with a competition between populations of agents carrying contradictory statements, where the fuzziness is represented as a probability that a given agent carries a given statement or its negation. A debate in the society of such agents results in a victory of more or less immediate adherents of a particular solution.

The Society-of-Agents inhabits a working memory implemented as a kind of recurrent neural network proposed by Buller as a Neural Screen [5][6]. Each agent--member of the society is a binary word navigating all over the working memory and interacting with other agents. As it was shown in [7][8], owing to special properties of the agents and the working memory, the society is able to provide appropriate decision based on given measurements an statements stored in a Fuzzy Knowledge Base.

In the following sections a model of the proposed Society-of-Agent-based Fuzzy Controller, as well as some results of problem solving simulation based on the model is discussed.

2. The model

The proposed Society-of-Agent-based fuzzy controller, as Fig. 1. shows, consists of (a) an Input/Output device (I/O) (b) Fuzzy Knowledge Base, (c) Indoctrinator, (d) Working Memory, and (e) Poll device. However, as an illustration to the mathematical description, the more detailed Fig. 2. is useful.

Let us assume that T = {1, 2, ... } is a space of discrete values of time.

2.1. *Input/Output* device for each t belonging to T provides a set of measurements X_1, ..., X_n and receives calculated decisions. Let us assume that A_1, ..., A_M are facts related to the measurements, while A_{M+1}, ..., A_{M+m} are to be deduced. All As are interpreted as fuzzy sets.

2.2. *Fuzzy Knowledge Base* provides the functions ψ and μ and a set of rules S_1, ..., S_m. Ψ returns the number of a measurement being a member of the fuzzy set of a given number, while μ returns the value of the membership of a given measurement to a given fuzzy set. A given S_i is a pair $<y_i, Y_i>$, where y belongs to {A_{M+1}, ..., A_N}, while Y_i is a subset of {A_1, ..., A_N}.

2.3. *Indoctrinator* generates statements to be carried by agents as their opinions. It consists of two pattern generators and a Pattern Scheduler (see Fig. 2). The Pattern Generator I, produces patterns representing statements associated with received measurements in such a way, that the

probability of the apperance of a given statement A_i in the i-th outlet equals the membership of the related measurement to the fuzzy set A_i, while the probability of the apperance of the negation of the statement in the i-th outlet equals one minus the membership value (see Fig. 3). Pattern Generation II produces patterns representing rules. The function describing its output is constatns. The Pattern Scheduler enables user to regulate the density of the stream of patterns being introduced to the Working Memory via particular channels. Hence the Indoctrinator's output is described by the function $f':\mathbf{T}\rightarrow\varnothing \cup \{A_1, ..., A_n\} \cup \{\sim A_1, ..., \sim A_n\} \cup \{S_1, ..., S_m\}$ such that for j=1, 2, ..., K:

$$P(f'_j(t)\neq\varnothing) = r,$$
$$P(f'_j(t)=f_i(t) \mid f'_j(t)\neq\varnothing) = e_i/(e_1+e_2+...+e_{M+n}),$$

where:

$\sim A_i$ - not A_i,
K - number of inputs to the Working Memory,
P() - probability,
r - statement stream density (set by user),
$e_1, e_2, ...$ - importance factors (set by user),
$f_i:\mathbf{T}\rightarrow\{A_i, \sim A_i\}$ - an auxiliary function such that for i=1, 2, ..., M:

$$P(f_i(t)=A_i) = \mu_{A_i}(X\psi_{(i)}),$$
$$P(f_i(t)=\sim A_i) = 1 - \mu_{A_i}(X\psi_{(i)}),$$

while for i=M+1, M+2, ..., M+m, $f_i(t) = S_{i-M} = const.$

2.4. *Working Memory* constitutes an environment in which the Society of Agents lives. Let us consider a model of Working memory being an array of processing nodes, where each node can receive/send binary words from/to its nearest neighbors (or from/to itself, especially when a given neighbor is damaged or does not exist at all). Depending on the form and sophistication of the information to be processed, the nodes may be implemented either as fully designed digital systems or as neural networks. In this paper a sample 2-dimensional environment in which each processing node has bidirectional connections to four neighbors (see Fig.4) is discussed.

The Indoctrinator provides agents with opinions. Some of the opinions may be contradictory. A given agent may navigate passing consecutive nodes and interact with other agents it can meet. Especially essential is the interaction between an agent carrying a rule and an agent carrying a related fact. In such case the first agent will replace the rule with a logical conclusion from the opinions of the two agents. Such interactions may take place in several nodes at the same time. Hence, in a period of time one may observe an appearance of a group of agents having an opinion which might be recognized as a final conclusion, as well as agents having an opposite opinion. After a period of unstable situation, adherents of a particular solution should win.

2.5. *Poll device* is a filter collecting continuously agent's opinions, and, based on a mean results for an appropriate period of time, to perform (or to stop performing) appropriate actions.

3. Strategy of agent's behavior

The first efficient strategy of agent's behavior was discovered via gradual improving of an inefficient initial strategy by a process of "trial and error" using a simulation model of Jigsaw Machine [7] and formalized for further analysis [6][8]. As a given agent is to navigate and interact with other agents, the strategy of the agents behavior consists of two rules: NAVIGATION RULE and INTERACTION RULE described here from an agent's point of view.

NAVIGATION RULE

Assuming that:

(i) having entered a processing node you can "see" a left-hand gate, a gate in front of you, a right-hand gate and a gate behind you (i.e. the gate you entered through),

(ii) E is a set of agents you have met in the processing node,

(iii) LRAT, FRAT, and RRAT are the agents who might enter the node through your left-hand gate, the gate in front of you, and your right-hand gate respectively,

if E={LRAT, RRAT} or E={}	(c1)
then go forward	(a1)

    (i.e. exit the node through the gate in front of you),

if FRAT belongs to E	(c2)
then	
* let R=FRAT, then	(a2)
* apply the INTERACTION RULE, and then	(a3)
* turn back	(a4)

  (i.e. exit the node through the gate behind you),

if E={LRAT} or E={RRAT}	(c3)
then	
* let R=LRAT or R=RRAT, respectively, then	(a5)
* apply the INTERACTION RULE, and then	(a6)
* turn right or left respectively	(a7)

  (i.e. exit the node through your right-hand gate or left-hand gate, respectively).

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INTERACTION RULE

Assuming that a G initially equal 0 is assigned to each agent at the moment of joining the
Society, R is the agent defined in the NAVIGATION RULE (see action a2 and a5), y and Y are
"your y" and "your Y" respectively, y' and Y' are "R's y" and "R's Y" respectively, and ~y means
"not y",

if neither y' nor ~y' belongs to Y                                    (c4)
then
  if neither y nor ~y belongs to Y'                                   (c5)
  and [ G>G'                                                          (c6)
  or Y=Y'={} and y=~y' ]                                              (c7)
  then kill R                                                         (a8)
else
  if Y'={}                                                            (c8)
  then
  * let G=G+1, then                                                   (a9)
  * if y' belongs to Y                                                (c9)
    then let Y=Y-y'                                                   (a10)
  else
  * let y=~y, then                                                    (a11)
  * let Y={}.                                                         (a12)
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Owing to the NAVIGATION RULE a given agent is able to change the direction of its motion as
often as the condition c2 or c3 is satisfied. This resembles an elastic collision of balls on the
snooker table or, for a longer period of time, Brownian movements. Hence, the agent has a good
chance to visit any processing node and meet an appropriate mate in a reasonable time. In further
research a changing a direction of agent's motion based not only on agent-agent collisions may be
considered.

To prevent the Society from a congestion, non-prospective agents are eliminated. The
proposed criterion of survival/elimination is the G-factor. The higher G, the bigger chance for
survival, as an agent of higher G can kill the encountered one when their informational contents
has nothing in common (cf conditions c4, c5 and c6 for the action a8). The G-factor increases
after each successful production of a concluding information (conditions c4, c8 and the action
a9).

4. Sample problem solving

Let us assume that I/O provides the one-element set of measurements $\{T=55^{o}C\}$, while the Fuzzy Knowledge Base provides the rules: "alarm if not ok" and "ok if warm and not hot", as well as the data: $\psi(1)=\psi(2)=1$, $\mu_{warm}(55^{o}C)=.9$, $\mu_{hot}(55^{o}C)=.5$. The question is: To raise alarm or not? In such case the Indoctrinator produces four streams of statements:

<warm>/<~warm>,
<hot>/<~hot>,
<alarm, {~ok}> and
<ok, {warm, ~hot}>

and introduces the statements into the Society of Agents as the agent's opinions following the probability conditions described in the section 2.3.

A simulation model of a 10x10-node working memory with 9 input channels has been tested as the problem solver with $r=.5$ and the stream importance factors equal to 2, 2, 1, 3 respectively. Fig. 5 shows the poll results for 5 consecutive experiments conducted for each of the temperatures: $45^{o}C$, $50^{o}C$, $53^{o}C$ and $55^{o}C$, with the other membership values stored in the Fuzzy Knowledge Base were: $\mu_{warm}(45^{o}C)=.9$, $\mu_{hot}(45^{o}C)=.1$, $\mu_{warm}(50^{o}C)=.95$, $\mu_{hot}(50^{o}C)=.3$, $\mu_{warm}(53^{o}C)=.94$, and $\mu_{hot}(53^{o}C)=.41$. As Fig. 5 shows, in all cases after about 300 cycles the poll results converged to values over 60% or under 35%, which suggests that the discussed way of fuzzy inferencing is more decisive than the classic fuzzy calculus. However, one may note that while for $T=45^{o}C$ and $T=50^{o}C$ the suggested final decision was "not alarm", for $T=53^{o}C$ for four times the poll result converged to over 60% ("alarm") while once to under 20% ("not alarm").

5. Concluding remarks

In the age of cheap chips, one may anticipate the possibility of employment of massively parallel algorithms on the level of small single controller. The proposed paradigm replaces classic fuzzy calculus with a competition between populations of agents carrying contradictory statements and may play in fuzzy knowledge processing similar role as the Monte Carlo method in digital integration. The Society-of-Agents-based fuzzy controller, when simulated, seems to be more decisive than the classic fuzzy calculus.

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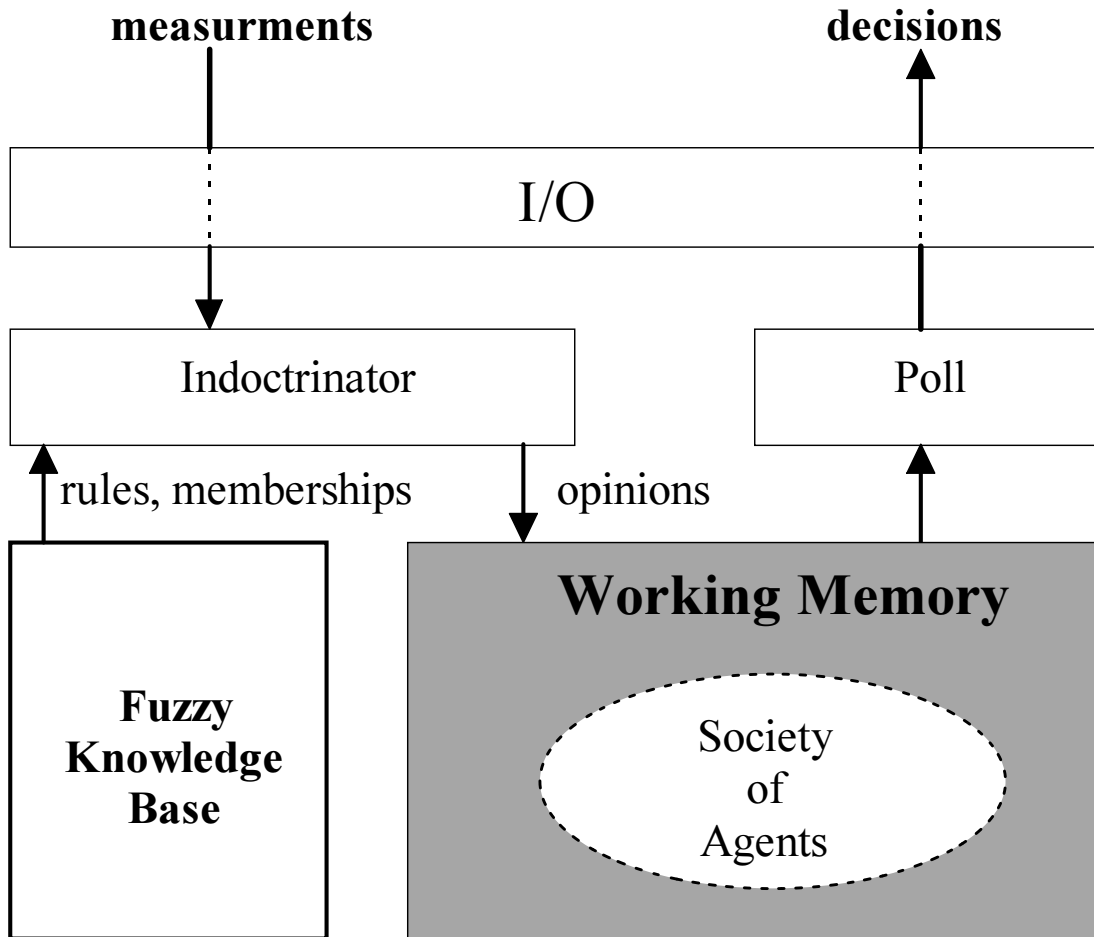
measurments   **decisions**

I/O

Indoctrinator   Poll

rules, memberships   opinions

**Fuzzy
Knowledge
Base**

Working Memory

Society
of
Agents

Fig.1. Society-of-Agents-based Fuzzy Controller: A conceptual model.

measurements

Fuzzy Knowledge Base

X_1 $\quad$ X_2 $\quad$ . . . . $\quad$ X_n $\quad\quad$ μ $\quad$ ψ $\quad\quad$ S_1 $\quad$ S_2 $\quad\quad$ . . . . $\quad\quad$ S_m

Pattern Genarator I $\quad\quad\quad$ Pattern Generator II

f_1 $\quad$ f_2 $\quad$ . . . . $\quad$ f_M $\quad$ f_{M+1} $\quad$ f_{M+2} $\quad\quad$ . . . . $\quad\quad$ f_{M+m}

r
$\quad$ Pattern Scheduler
e

f_1' $\quad$ f_2' $\quad\quad$ . . . . $\quad\quad$ f_K'

Neural Screen

f_1'' $\quad$ f_2'' $\quad\quad$ . . . . $\quad\quad$ f_L''

Filter

U_1 $\quad$ U_2 $\quad\quad$ . . . . $\quad\quad$ $U_{N\text{-}M}$
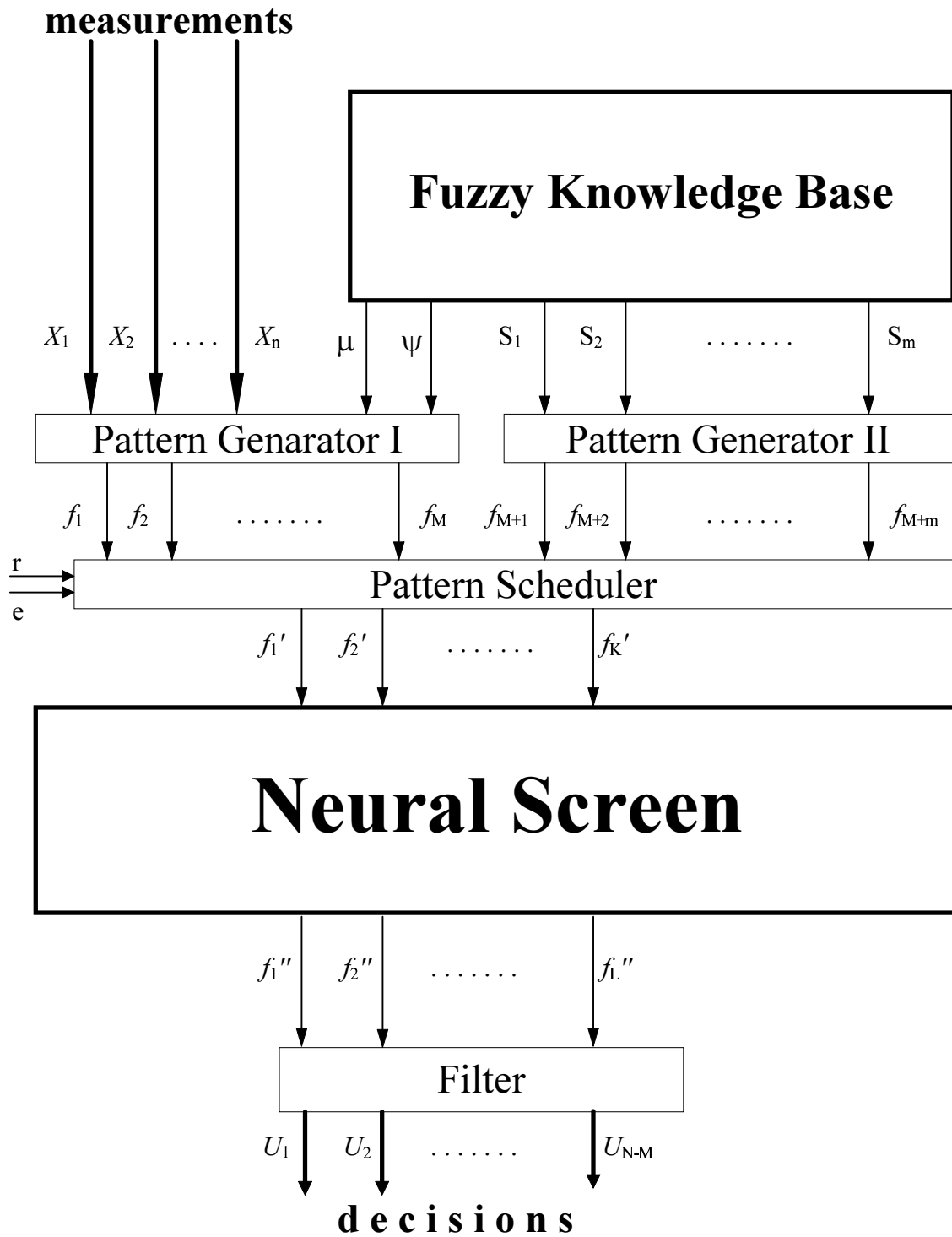
d e c i s i o n s

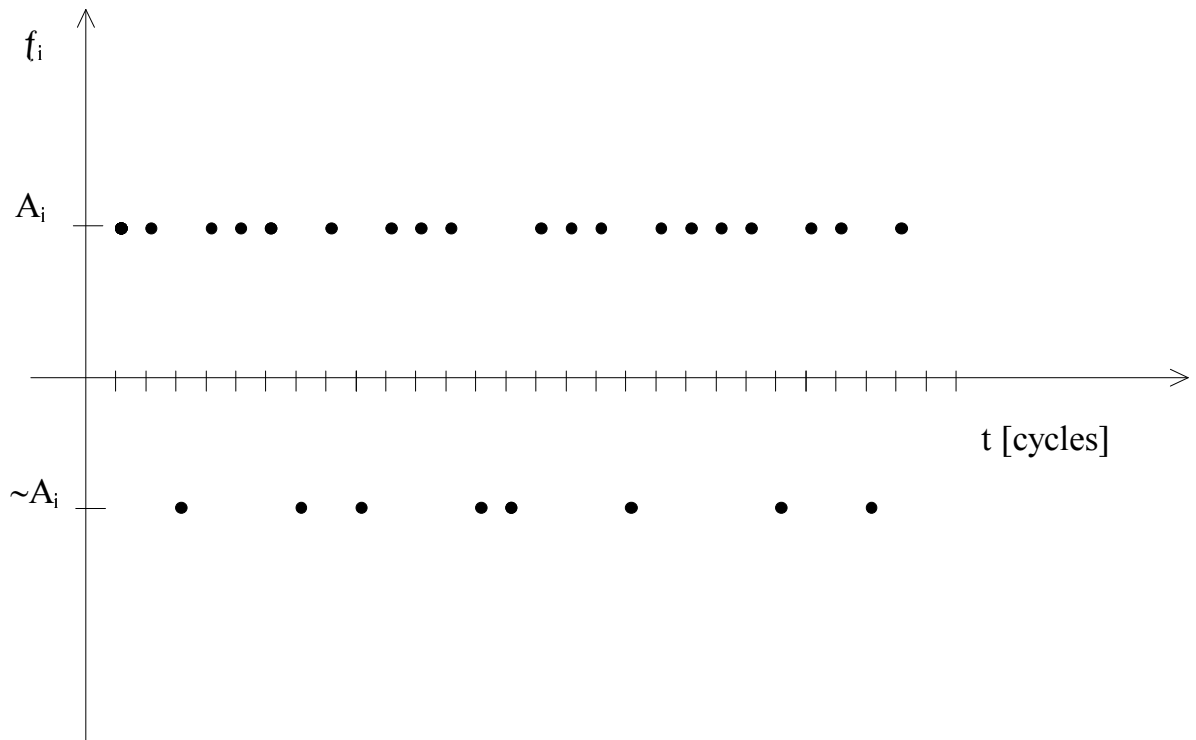Fig. 2. Society-of Agents-based Fuzzy Controler: Basic components

Fig. 3. The sample plot of the discrete function f_i. The probability that for a given moment t the function f_i returns A_i, equals the value of the membership of the related measurement to the fuzzy set A_i . This is the novel representation of fuzziness for the Monte Carlo-like massively parallel fuzzy inferencing.
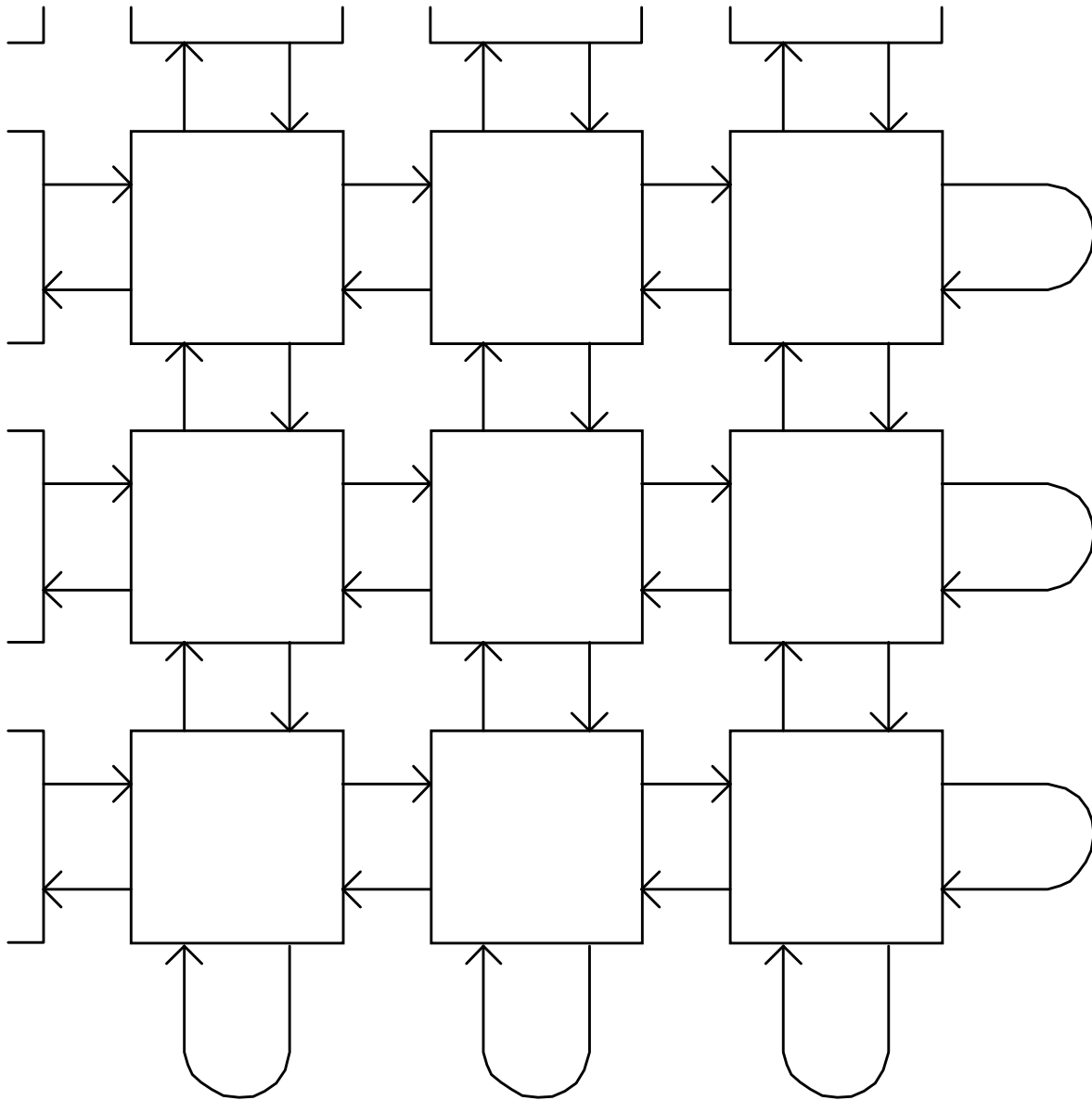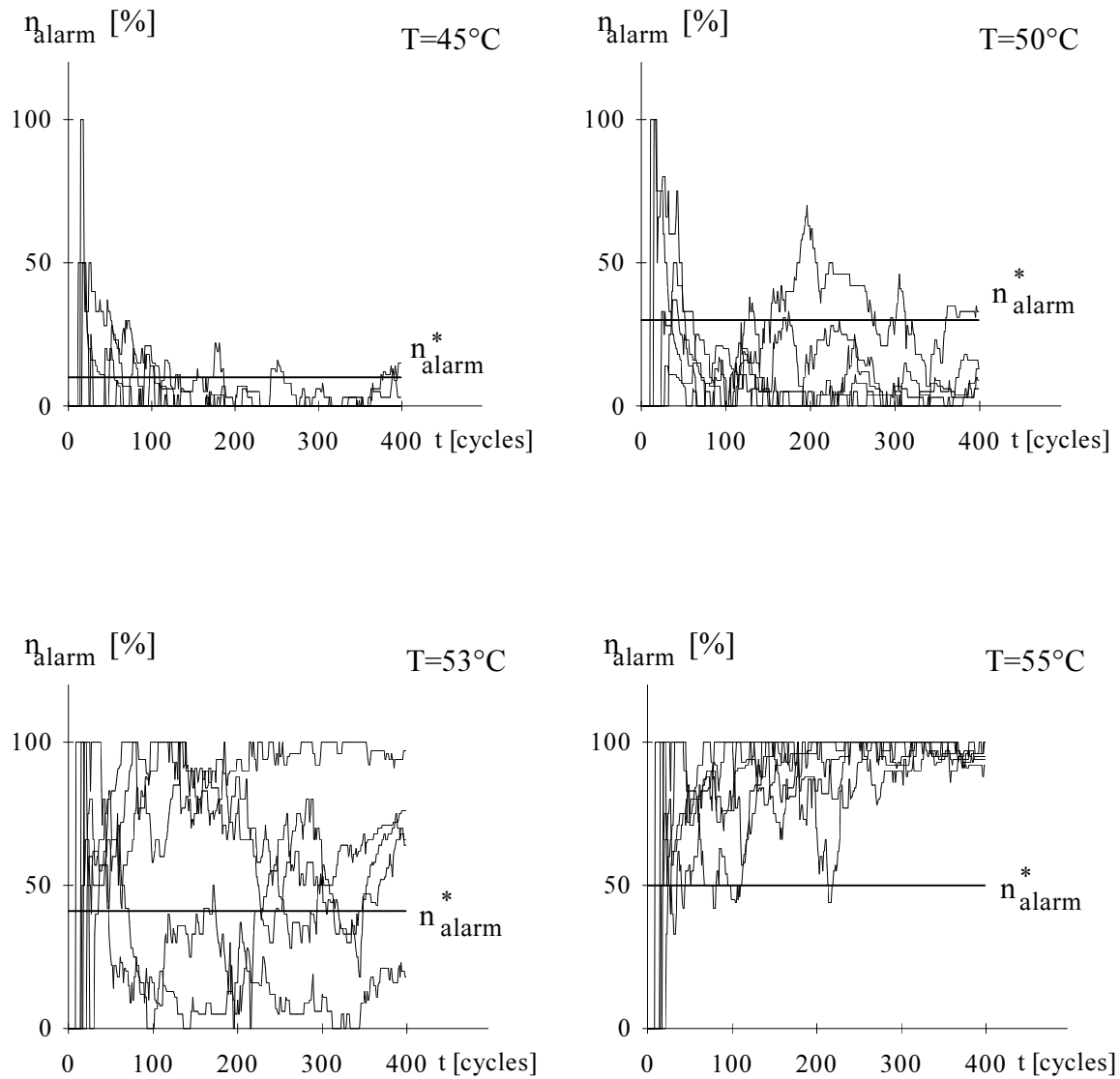
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Fig.4. A sample structure of Working Memory

Fig. 5. The varying poll results. For each of the selected temperatures five independent experiments has been done. n_{alarm} - percentage of agents having opinion „alarm” in the population of agents having opinion „alarm” or „not alarm”, n^{*}_{alarm} - the membership of T to the fuzzy set „alarm” calculated using classic set-theoretic operations and multiplied by 100 ([3]).