Innovative Types and Abilities of Neural Networks Based on Associative Mechanisms and a New Associative Model of Neurons

Adrian Horzyk

horzyk@agh.edu.pl

AGH

AGH University of Science and Technology

Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering

Department of Automatics and Biomedical Engineering

Poland, 30-059 Krakow, Mickiewicza Av. 30, C3/205

http://home.agh.edu.pl/~horzyk/index-eng.php

This is the story about associative processes that take place in a human mind and can be modeled in artificial neural associative systems that can form knowledge and behave intelligently…

What will be this presentation about?

About association, intelligence, knowledge, neurons, big data … and a small lovely monkey!

What will be this presentation about?

About association, intelligence, knowledge, neurons, big data … and a small lovely monkey!

PROCESSING BIG DATA?

Proces BIG DATA
with BIG EFFORT
on many computers
to retrieve some information?

OR

Transform BIG DATA
to BIG KNOWLEDGE
and retrieve some
information using it?

BRAINS – BIG DATA MACHINES

- efficient machines for big data processing
- do not remember all data
- form knowledge on their basis
- automatically programmed by the data via senses and various types of receptors

WHAT DO WE KNOW ABOUT A BRAIN?

✓ **It is working all the time throughout its whole life.**

✓ **When asked it usually answers immediately if it can recall the answer to a given question.**

✓ **We can ask: „*What do you associate with Poland?*" instead of „*What do you know about Poland?*"**

✓ **Can we use word „*associate*" as a synonym for „*know*"?**

✓ **If you do not associate something you also don't know it.**

✓ **It contains a huge amount of neurons and glia cells that are in the cerebral spinal fluid.**

Are brains slow or fast?

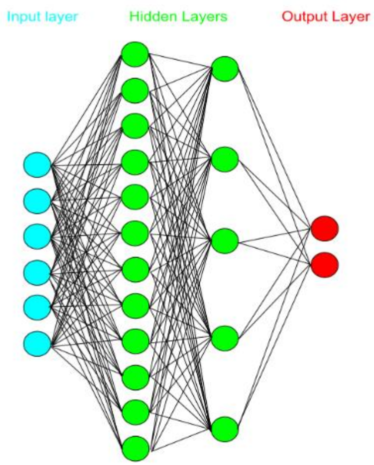
HOW FAST OUR BRAINS WORK?

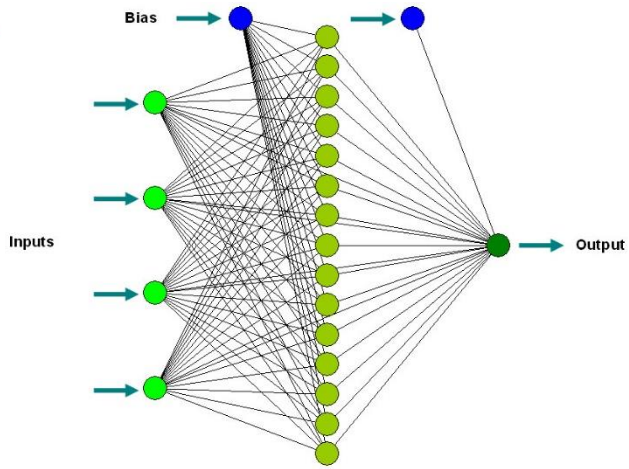
- A usuall reaction for sensorial stimuli of a brain is produced in about 300 – 1100 ms.
- Biological neurons are usually activated 12 – 30 times per second, so they are activated again after 33 – 83 ms.
- In result, such neurons can be sequentially activated only about 4 – 25 times when producing an inteligent output reaction on initial stimuli.
- Our brains have no time to loop huge amouts of stored data or search for information in data tables in the way that is often and usually used in computer science: ~~FOR, FOREACH, WHILE, REPEAT, DO…WHILE~~

CONCLUSION: Our brains should use another computational model to achieve and proces necessary information so fast!

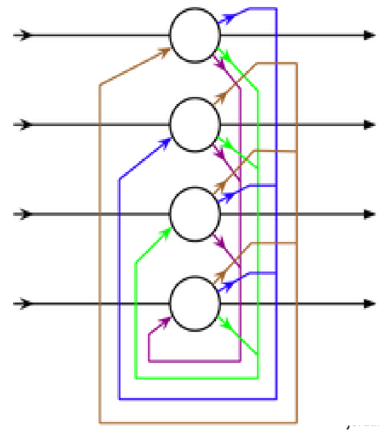
What kinds of neural networks we can already train?

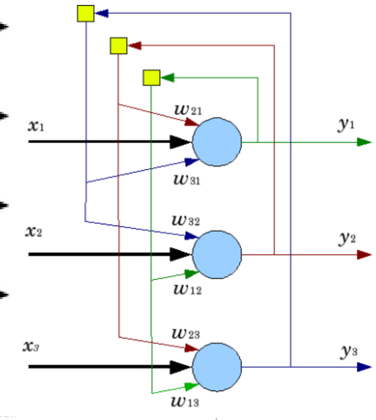
Multilayer Feedforward Neural Networks



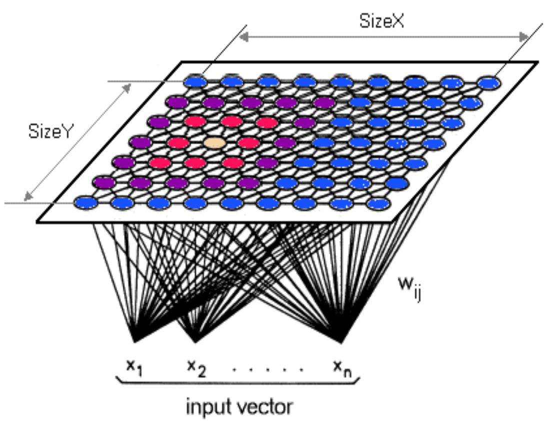


Recurrent Neural Networks

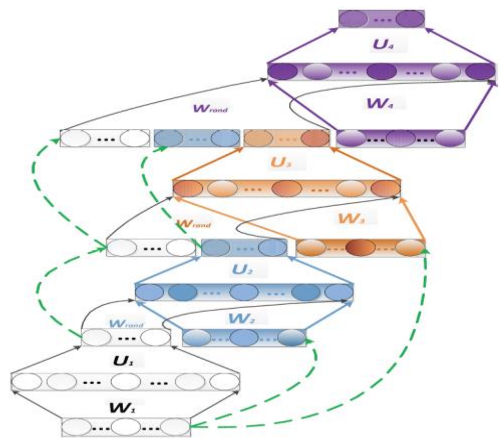




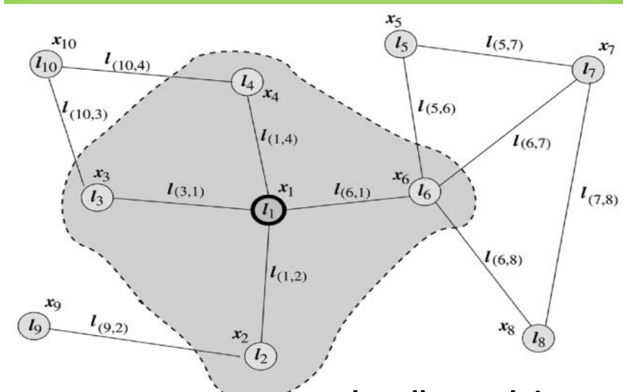
Self Organizing Maps



Deep Neural Networks



Graph Neural Networks



can handle graph inputs

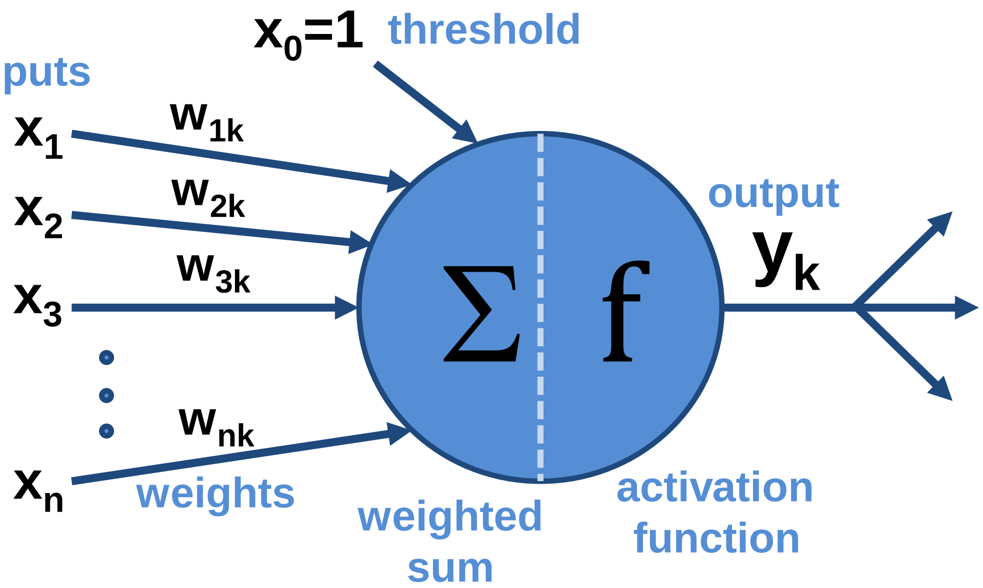
$$x_1 = f_w(\underbrace{l_1, l_{(1,2)}, l_{(3,1)}, l_{(1,4)}, l_{(6,1)}}_{l_{co[1]}}, \underbrace{x_2, x_3, x_4, x_6}_{x_{ne[1]}}, \underbrace{l_2, l_3, l_4, l_6}_{l_{ne[n]}})$$

Can we already create and train brain-like graph neural structures to represent knowledge?

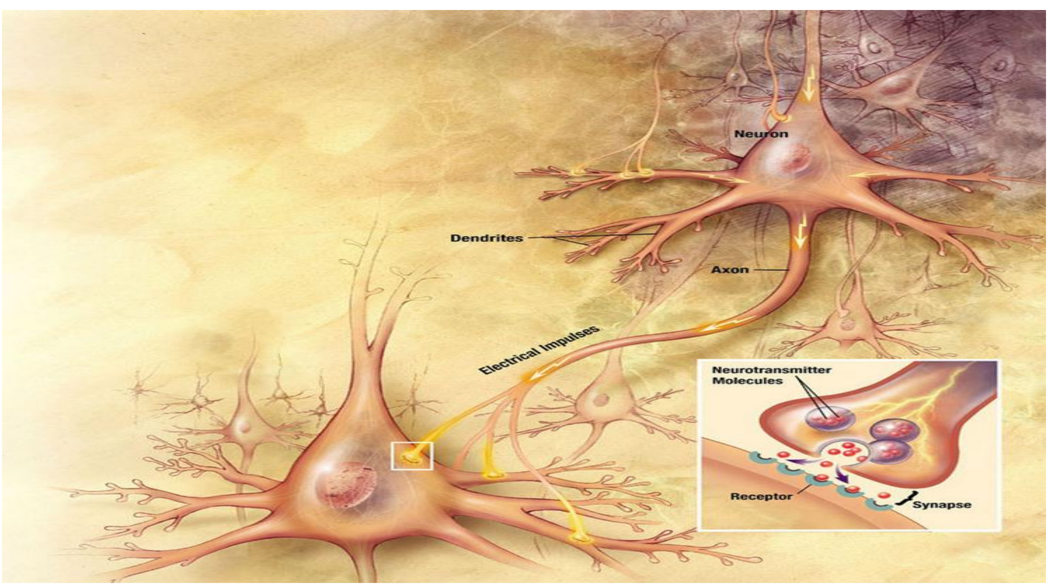
MAIN APPROACHES IN NEURON MODELING

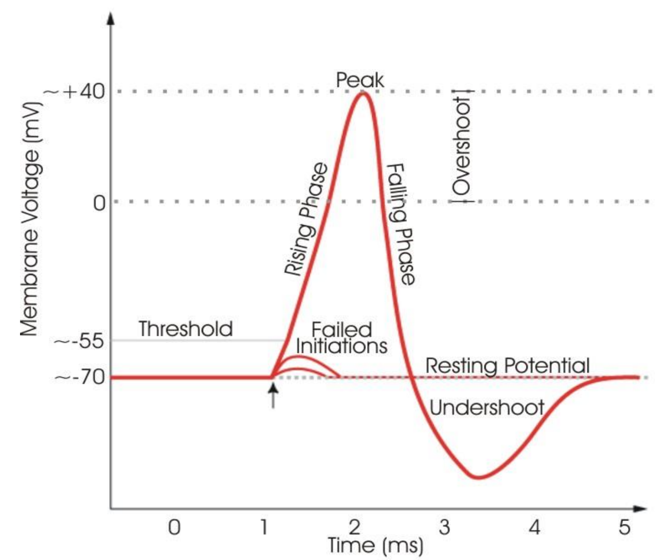
1. Artificial Neurons

$$y_k = f\left(\sum_{i=0}^{n} w_{ik} x_i\right)$$



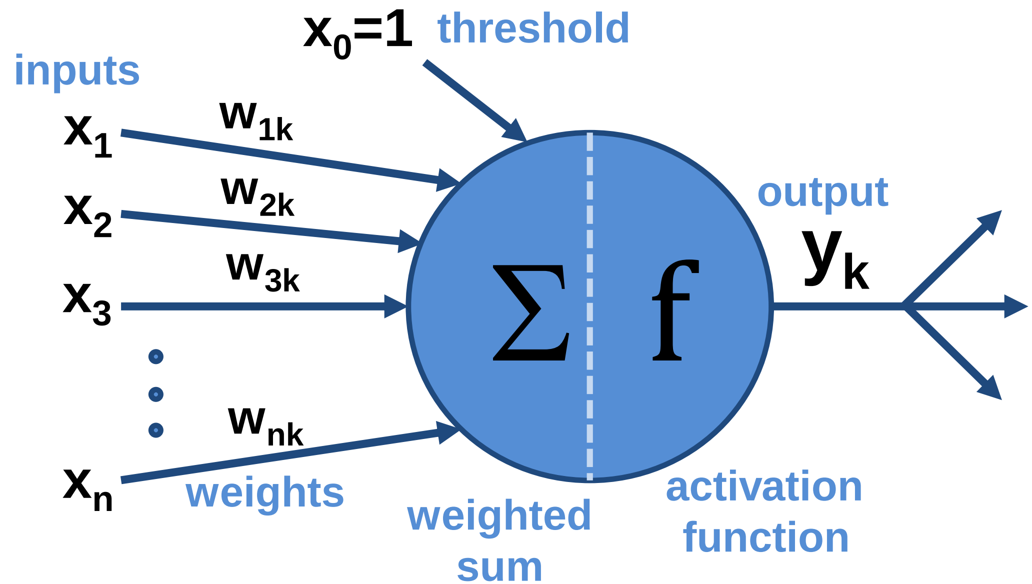
2. Spiking and Non-Spiking Neurons





ARTIFICIAL NEURON MODELS

$$y_k = f\left(\sum_{i=0}^{n} w_{ik} x_i\right)$$



All inputs usually <u>simultaneously</u> influence on a neuron.

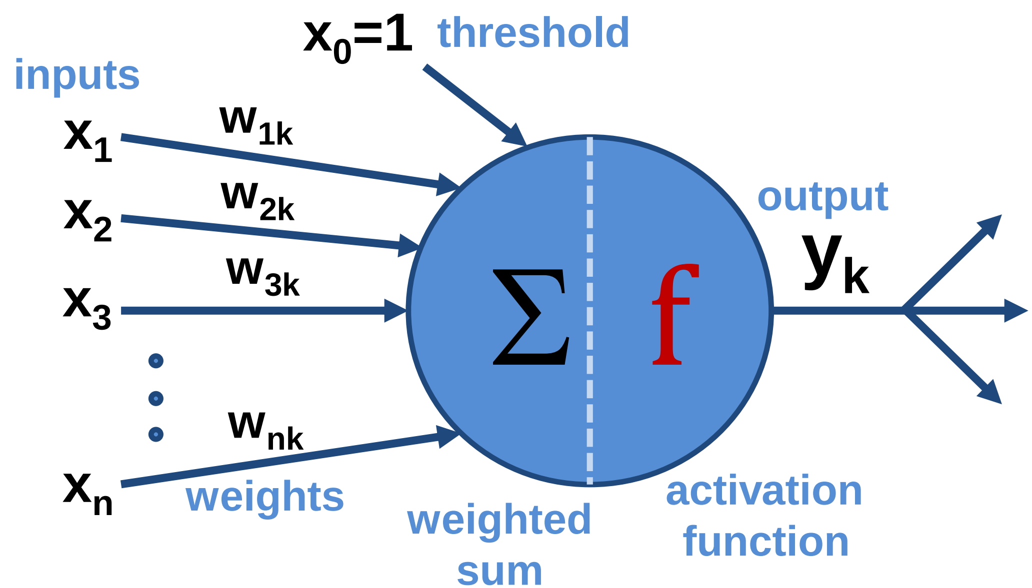
The previous states of a neuron <u>do not impact</u> on its current state.

No <u>time dependencies</u> between states are taken into consideration.

All stimulation and operation processes happen immediatelly <u>without any interval.</u>

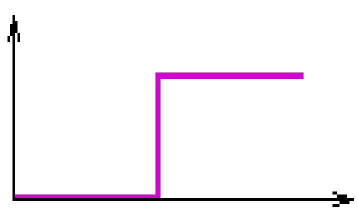
ARTIFICIAL NEURON MODELS

$$y_k = f\left(\sum_{i=0}^{n} w_{ik} x_i\right)$$



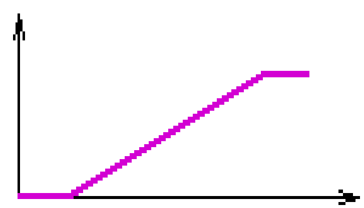
Variety of Activation Functions of Artificial Neurons

Threshold/Step Functions f
with binary outputs



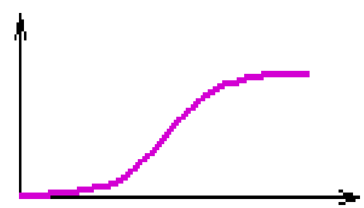
Threshold

Linear Functions f
with graded outputs



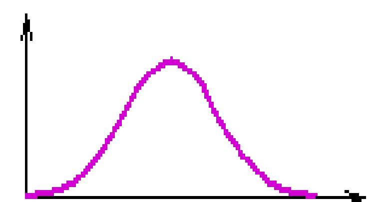
Linear

Sigmoid Functions f
with graded outputs



Sigmoid

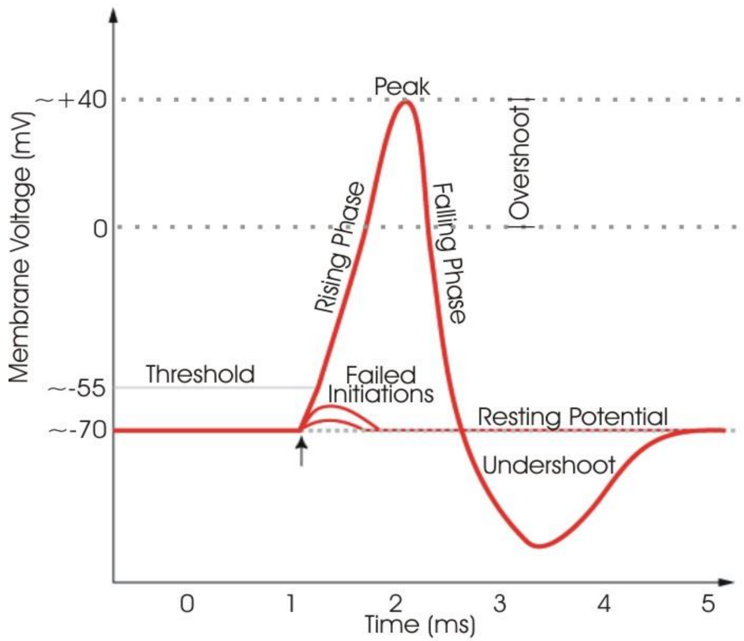
Gaussian Functions f
with graded outputs

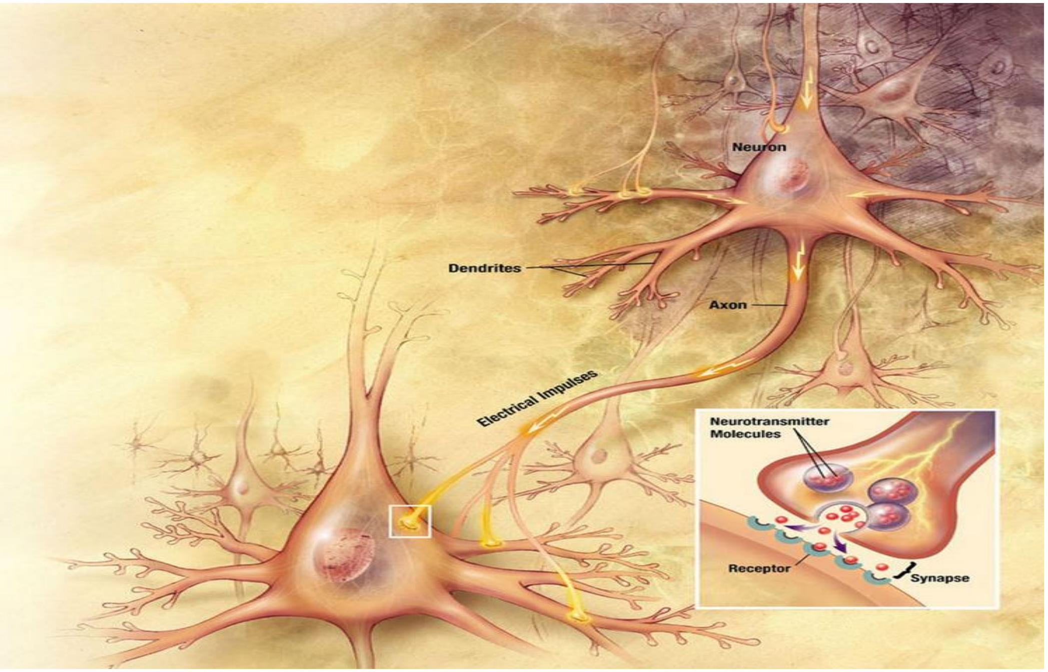


Gaussian

The functions with a graded outputs are usually used for approximation or clusterization of training data in classification tasks.

SPIKING AND NON-SPIKING NEURONS





- Used to construct spiking neural networks (SNN)
- Incorporate the <u>concept of time</u> into their operating model.
- Fire when a membrane potential reaches a <u>threshold value</u>.
- Fundamental question of neuroscience is to determinate if neurons communicate by <u>a rate or temporal code</u>?
- They have proved useful in neuroscience, but not yet in engineering!

AS-NEURONS & ACTIVE ASSOCIATION

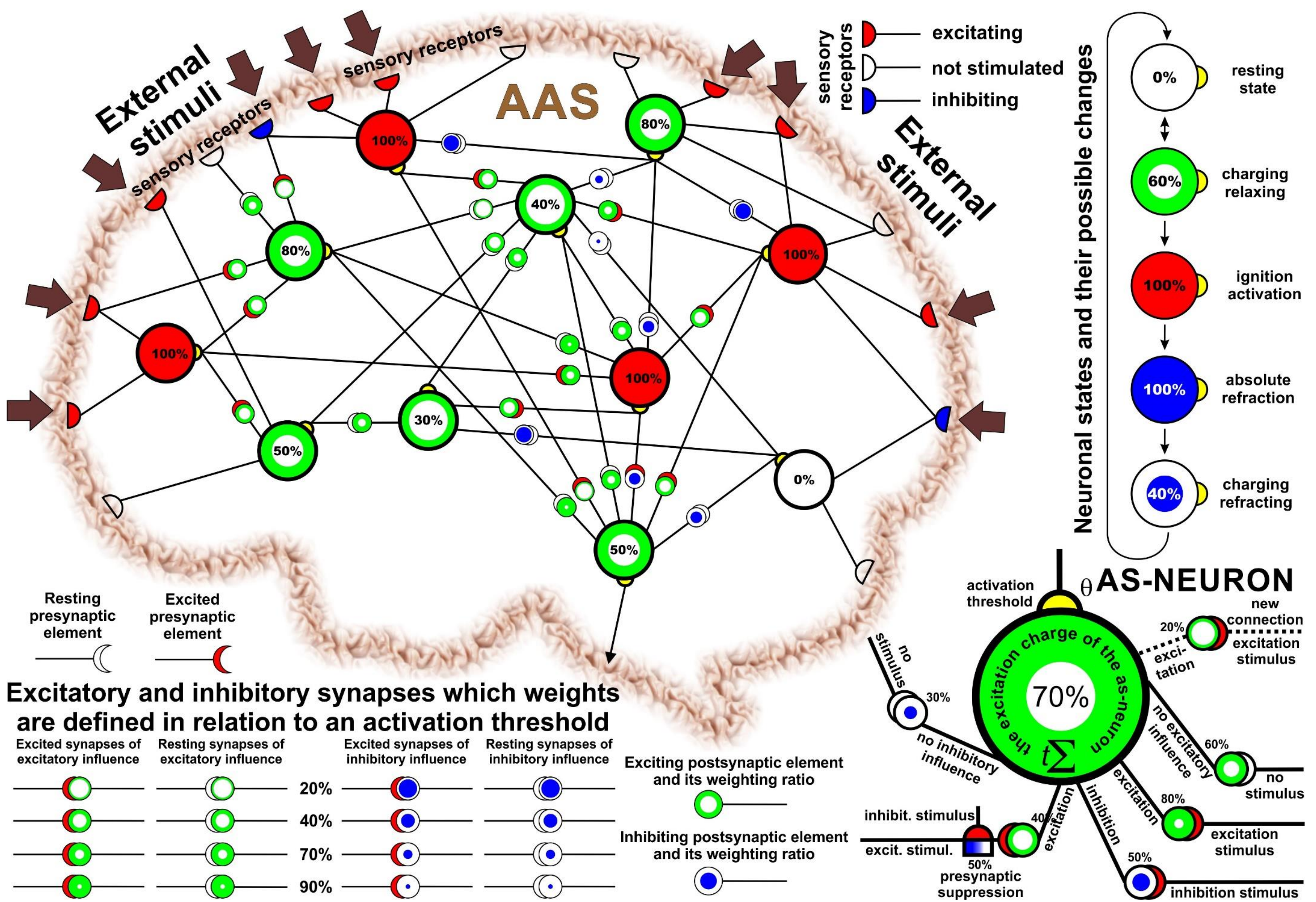
ARTIFICIAL NEURONS

associative
AS-NEURONS

SPIKING NEURONS

- ✓ **Relax and refract in time (time dependent).**
- ✓ **Connect to other as-neurons automatically (plasticity) to reflect various relations between data (associate).**
- ✓ **Represent all time-spread combinations of input stimuli <u>that activate them</u>.**
- ✓ **Represent objects semantically in a context of other connected neurons or receptors (semassel – semantic associative element).**
- ✓ ***Each as-neuron represents a class of objects or their part when it activates as a result of a time-spread combination of input stimuli triggered by any object of this class.***

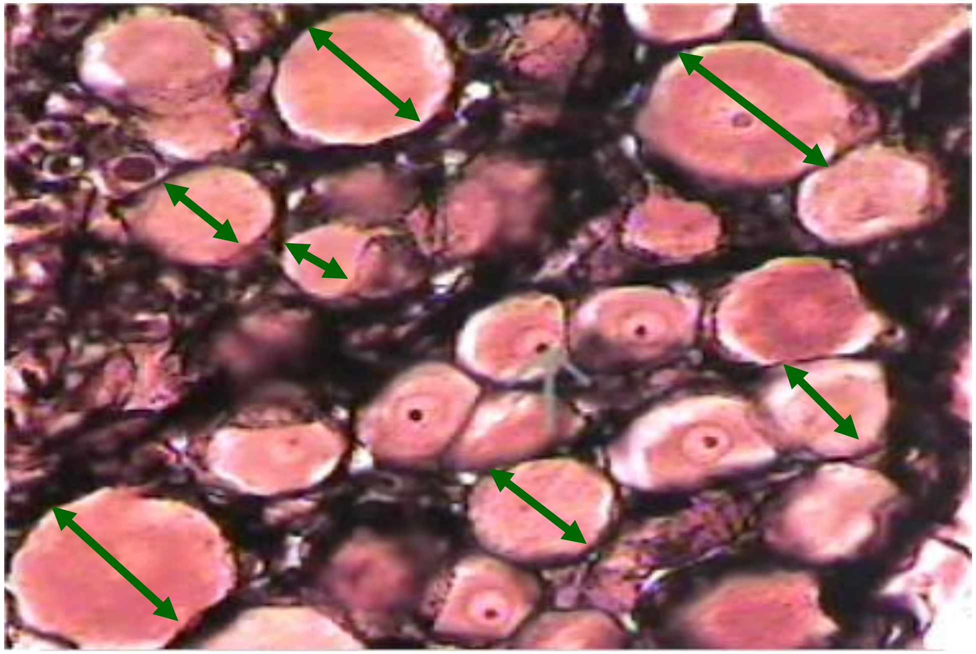
AS-NEURONS – What should they model?

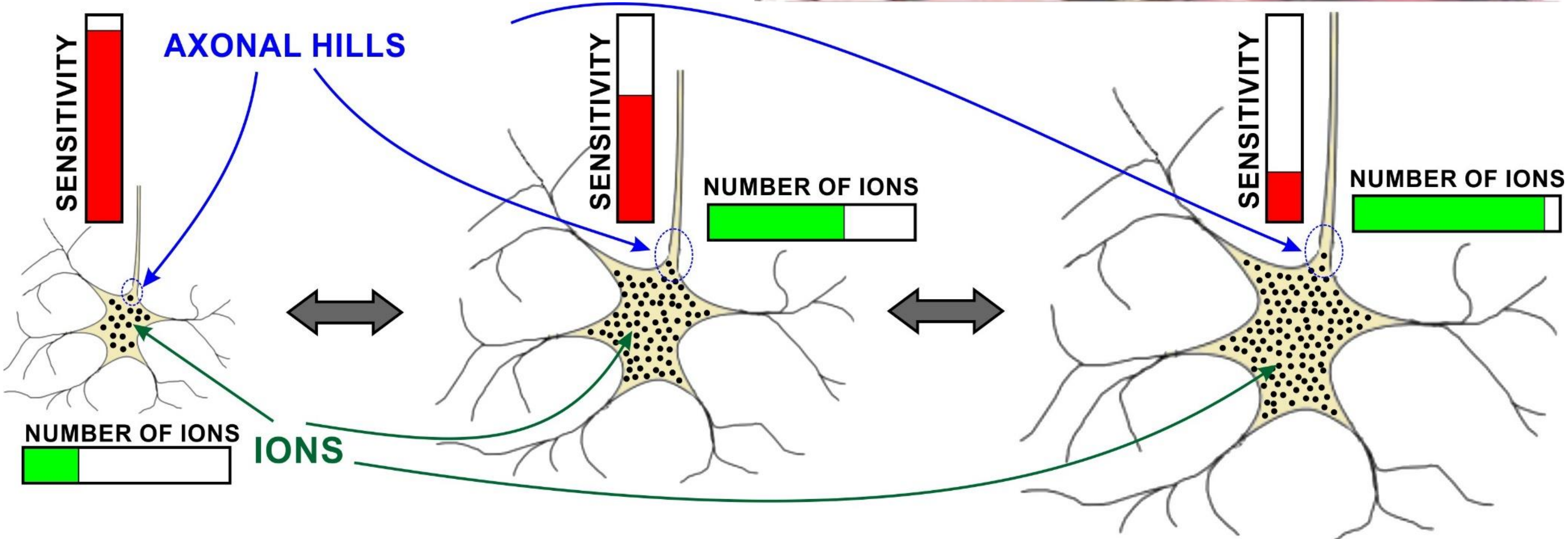


PLASTICITY AND GROWTH OF NEURONS

Biological neurons differ in:

- size and internal capacity
- sensitivity and reactivity for input stimuli
- represented subsets of input stimuli that activate them
- connections and weights…



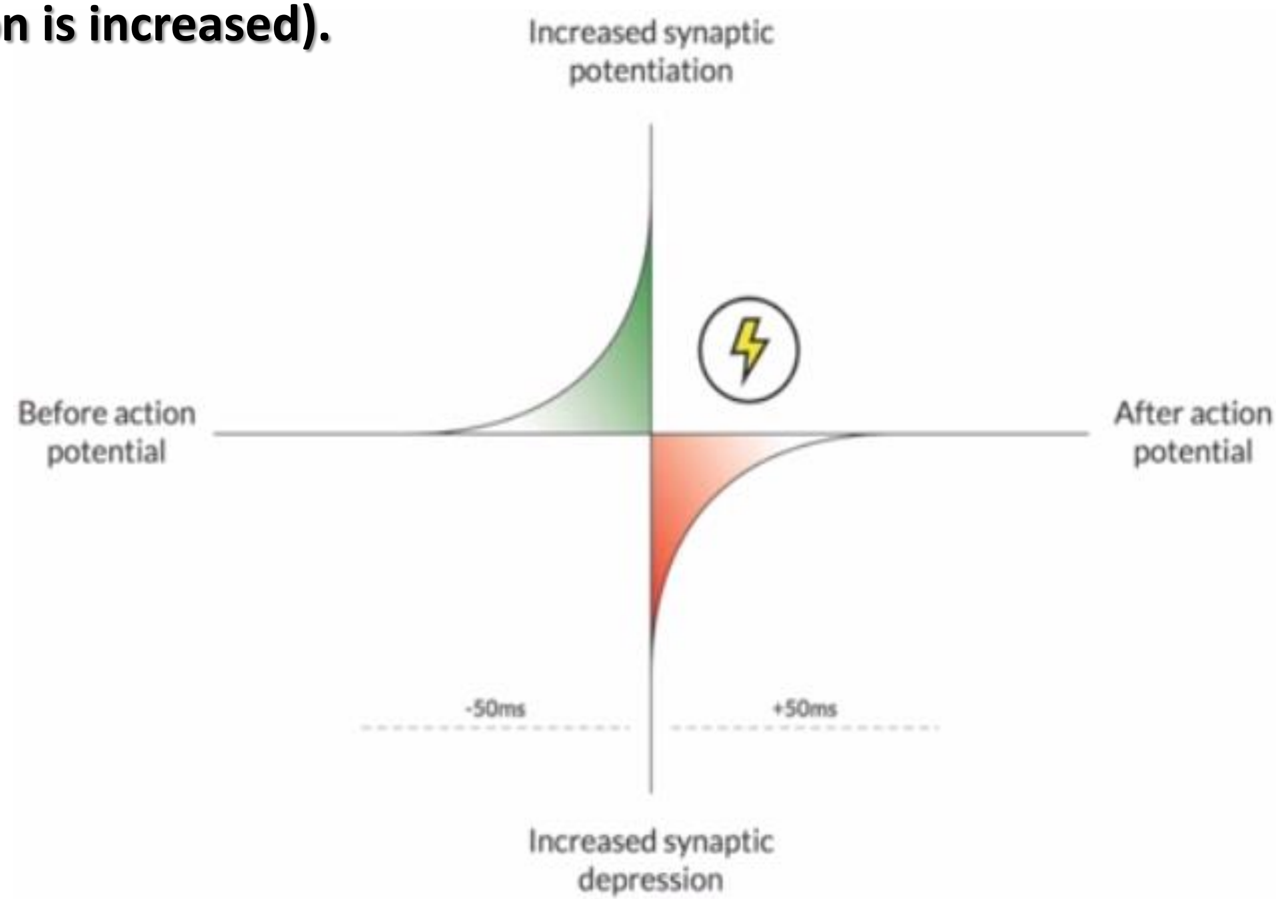


FREQUENCY OF ACTIVE REATIONS

- ✓ Neurons can be activated
  when their charge and attain an activation threshold.
- ✓ Not every combination of input stimuli activate them.
- ✓ Active reaction of a neuron gives it a possibility to quickly influence other connected neurons.
- ✓ Active reactions of neurons activate plasticity and reinforcement processes in synapses.
- ✓ The lack of active reaction of neurons can degrade and weaken input synapses and connections.
- ✓ Frequency of active reactions of neurons can influe their growth and change their sensitivity for next input stimuli.

OBSERVATIONS FROM NEUROBIOLOGY

- ✓ **Connections between neurons are automatically created and strengthen if their activity often occurs in short intervals (the synaptic potentiation is increased).**
- ✓ **Connections between neurons are automatically weaken if presynaptic activity of neurons often do not bring on activity of postsynaptic neurons (the synaptic depression is increased).**



EFFICIENCY OF SYNAPTIC CONNECTIONS

- ✓ Neurons can usually create many new synaptic connections.
- ✓ The creation proces of connections is conditional.
- ✓ We observe that neurons often activated in close interval connect, multi-connect, or reinforce synaptic weights.
- ✓ The reinforcement of a synaptic connection depends on how fast a postsynaptic neuron is activated after synapsis stimulation.

Efficiency of synaptic connections depends on:

- ➢ Frequency of successul activation of a postsynaptic neuron after synapsis stimulation.
- ➢ Depends on intervals between stimulation of synapsis and a moment of a postsynaptic neuron activation.

MODELING OF SYNAPTIC EFFICIENCY IN ANAKG-2

Synaptic efficiency between two connected and sequentially activated neurons is computed in accordance with each interval between a synaptic stimulus and a moment of postsynaptic neuron activation:

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S} \,:\, (\cdots \rightsquigarrow S \rightsquigarrow \cdots \rightsquigarrow \widehat{S} \rightsquigarrow \dots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t - t_a^{\widehat{S}}}{\omega}} \right)^{\gamma} \qquad (1)$$

$S \rightsquigarrow \widehat{S}$ - a synaptic weighted connection between presynaptic as-neuron S and postsynaptic as-neuron $\widehat{S}$

$\mathbb{S}$ - a training sequence set

ω - maximum time necessary to gradually relax each as-neuron from its most excited state to its resting state

$t_a^{\widehat{S}}$ - computed relative activation time of as-neuron $\widehat{S}$ according to its above-threshold excitation level determined by its activation threshold θ_S $(0 < t_a^{\widehat{S}} \leq t_a^{MAX})$

Δt - is an interval between synaptic stimulation and activation of postsynaptic as-neuron $\widehat{S}$

γ - influences the length of a context of previously activated as-neurons that are taken into account, $\gamma \geq 2$, usually $\gamma = 4$

WEIGHT COMPUTATION IN ANAKG-2

Synaptic efficiencies and frequencies of activations of presynaptic neurons are used to compute weights:

$$w_{S,\widehat{S}} = \frac{\eta_S \cdot \delta_{S,\widehat{S}} \cdot \theta_{\widehat{S}}}{\eta_S + (\eta_S - 1) \cdot \delta_{S,\widehat{S}}} \tag{2}$$

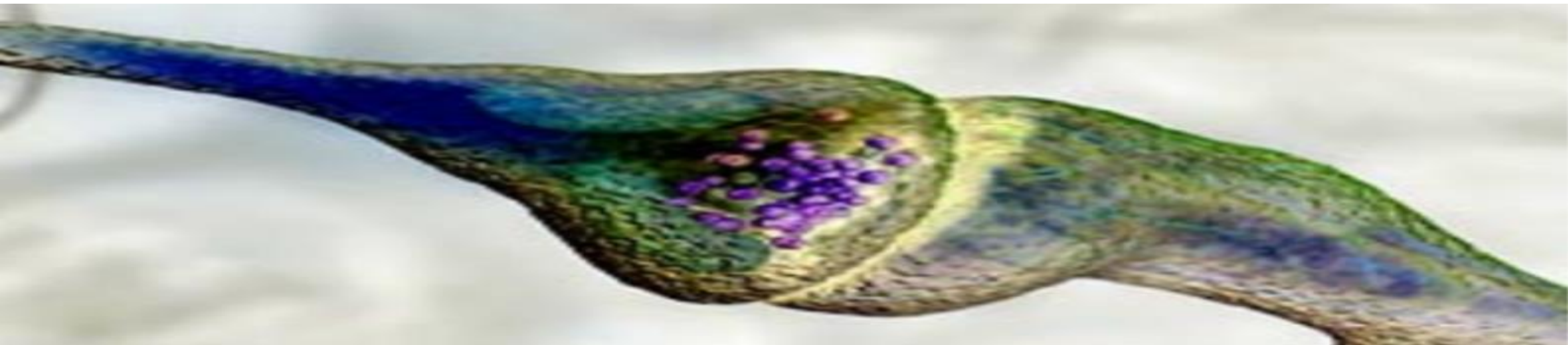
$w_{S,\widehat{S}}$ - a synaptic weight for connection $S \rightsquigarrow \widehat{S}$

$\delta_{S,\widehat{S}}$ - efficiency of synaptic connection at activating postsynaptic as-neuron $\widehat{S}$ through presynaptic as-neuron S accordingly to the time interval of their activations

η_S - a number of activations of presynaptic as-neuron S

θ_S - an activation threshold of as-neuron S

All weights can be computed after a single browse through a training sequence set!



COMPUTATION OF STATES OF AS-NEURONS IN ANAKG-2

Gradual relaxation of as-neurons allows to update the state of an as-neuron after a given time interval if this neuron has not been stimulated inside this interval:

$$X_{\widehat{S}}^{t_2} = g\left(X_{\widehat{S}}^{t_1}\right) = \begin{cases} \sum_{S \rightsquigarrow \widehat{S}} w_{S,\widehat{S}} \cdot x_S^{t_2} + R_{\widehat{S}}^{t_2-t_1}\left(X_{\widehat{S}}^{t_1}\right) & \text{if } \left|X_{\widehat{S}}^{t_1}\right| < \theta_{\widehat{S}} \\ \sum_{S \rightsquigarrow \widehat{S}} w_{S,\widehat{S}} \cdot x_S^{t_2} + R_{\widehat{S}}^{t_2-(t_1+t_r)}\left(-\theta_{\widehat{S}}\right) & \text{if } X_{\widehat{S}}^{t_1} \geqslant \theta_{\widehat{S}} \wedge t_2 > t_1 + t_r \\ -\theta_{\widehat{S}} & \text{if } X_{\widehat{S}}^{t_1} \geqslant \theta_{\widehat{S}} \wedge t_2 \leqslant t_1 + t_r \end{cases} \tag{5}$$

t_1 - the moment of the last update of a neuronal state

t_2 - the current moment of a neuronal state update and usually also the moment of a next input stimulus

t_r - absolute refraction time in which as-neurons are unsusceptible for any stimulations

t_s - time necessary to propagate a stimulus along a connection and through a synapse from presynaptic as-neuron S to postsynaptic as-neuron $\widehat{S}$

$R_{\widehat{S}}^{\Delta t}$ - a relaxation function that gradually turns as-neuron $\widehat{S}$ to its resting state

Δt - is the relaxation period from its last update during which no external stimuli occurred, $\Delta t = t_2 - t_1$

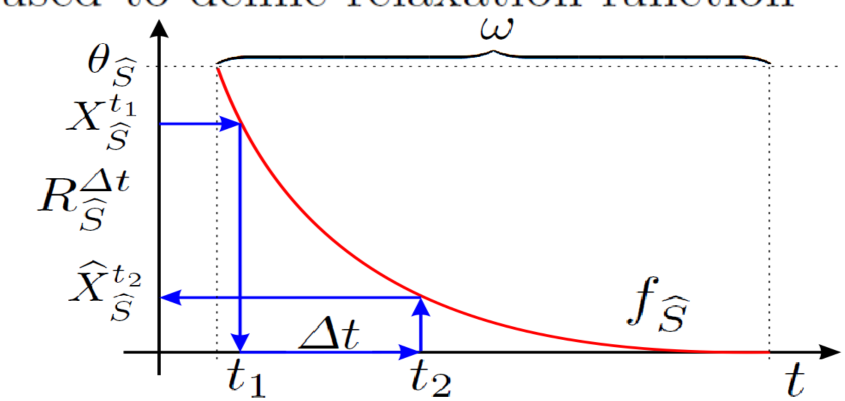
COMPUTATION OF STATES OF AS-NEURONS IN ANAKG-2

Relaxation function of as-neurons updates the state of an as-neuron after a given time interval if this neuron has not been stimulated inside this interval:

$$\widehat{X}_{\widehat{S}}^{t_2} = R_{\widehat{S}}^{\Delta t}\left(X_{\widehat{S}}^{t_1}\right) = \begin{cases} \operatorname{sgn}\left(X_{\widehat{S}}^{t_1}\right) \cdot f_{\widehat{S}}\left(f_{\widehat{S}}^{-1}\left(\left|X_{\widehat{S}}^{t_1}\right|\right) + \Delta t\right) = \\ = \operatorname{sgn}\left(X_{\widehat{S}}^{t_1}\right) \cdot \theta_{\widehat{S}} \cdot \left(\sqrt[\gamma]{\frac{\left|X_{\widehat{S}}^{t_1}\right|}{\theta_{\widehat{S}}}} - \frac{\Delta t}{\omega}\right)^{\gamma} & \sqrt[\gamma]{\frac{\left|X_{\widehat{S}}^{t_1}\right|}{\theta_{\widehat{S}}}} > \frac{\Delta t}{\omega} \\ 0 & \sqrt[\gamma]{\frac{\left|X_{\widehat{S}}^{t_1}\right|}{\theta_{\widehat{S}}}} \leq \frac{\Delta t}{\omega} \end{cases} \quad (4)$$

$f_{\widehat{S}}(t)$ - two concave continuously decreasing (during relaxation) or increasing (during refraction) functions used to define relaxation function R of as-neurons

$$f_{\widehat{S}}(t) = \begin{cases} \pm\theta_{\widehat{S}} \cdot \left(\frac{t}{\omega} - 1\right)^{\gamma} & 0 \leq t \leq \omega \\ 0 & t > \omega \end{cases} \quad (3)$$



γ - influences the length of a context of previously activated as-neurons that are taken into account, $\gamma \geq 2$, usually $\gamma = 4$

ω - maximum time necessary to gradually relax each as-neuron from its most excited state to its resting state

PRESYNAPTIC INFLUENCE AFTER ACTIVATION

The presynaptic as-neuron influences the postsynaptic as-neuron only if its excitation state has exceeded its activation threshold:

$$x_S^{t_2} = h\left(X_S^{t_2 - t_a^S - t_s}\right) = \begin{cases} 1 \text{ if } X_S^{t_2 - t_a^S - t_s} \geqslant \theta_{\widehat{S}} \\ 0 \text{ if } X_S^{t_2 - t_a^S - t_s} < \theta_{\widehat{S}} \end{cases} \qquad (6)$$

$x_S^{t_2}$ - an input stimulus distributed from as-neuron S to synapses, where t_2 is a moment of its influence on postsynaptic as-neurons via these synapses

$h(X_S^t)$ - a function that determines the presynaptic influence of as-neuron S accordingly to the activation threshold of this as-neuron

t_2 - the current moment of a neuronal state update and usually also the moment of a next input stimulus

t_s - time necessary to propagate a stimulus along a connection and through a synapse from presynaptic as-neuron S to postsynaptic as-neuron $\widehat{S}$

$t_a^{\widehat{S}}$ - computed relative activation time of as-neuron $\widehat{S}$ according to its above-threshold excitation level determined by its activation threshold θ_S $(0 < t_a^{\widehat{S}} \leq t_a^{MAX})$

SPEED UP ACTIVATION OF POSTSYNAPTIC AS-NEURON

Speed up of an activation moment of a postsynaptic as-neuron when the excitation state of this as-neuron exceeds its activation threshold:

$$t_a^{\widehat{S}} = T(X_{\widehat{S}}, \theta_{\widehat{S}}) = \left\lceil \frac{t_a^{MAX}}{1 + \frac{X_{\widehat{S}} - \theta_{\widehat{S}}}{\theta_{\widehat{S}}}} \right\rceil \qquad (7)$$

$$X_{\widehat{S}} = \sum_{t_2 \leq t \leq t_a^{\widehat{S}}} X_{\widehat{S}}^t$$

- t_2 - the current moment of a neuronal state update and usually also the moment of a next input stimulus
- $t_a^{\widehat{S}}$ - computed relative activation time of as-neuron $\widehat{S}$ according to its above-threshold excitation level determined by its activation threshold θ_S $(0 < t_a^{\widehat{S}} \leq t_a^{MAX})$
- t_a^{MAX} - maximum activation time of as-neurons when $X_S = \theta_S$
- $\theta_{\widehat{S}}$ - an activation threshold of as-neuron $\widehat{S}$

TRAINING SEQUENCES

1x	S1	E1	E2	E3	E1
1x	S2	E4	E5	E2	E6
1x	S3	E7	E5	E2	E8
1x	S4	E7	E9	E8	E6
1x	S5	E5	E1	E2	
1x	S6	E4	E2	E3	E5	E7

Horzyk, A., *Innovative Types and Abilities of Neural Networks Based on Associative Mechanisms and a New Associative Model of Neurons – the invited talk at the International Conference ICAISC 2015, Springer Verlag, LNAI 9119, 2015, pp. 26-38.*

CONSTRUCTION OF ASSOCIATIVE NEURAL GRAPHS

TRAINING SEQUENCES

S1 E1 E2 E3 E1 | S2 E4 E5 E2 E6 | S3 E7 E5 E2 E8
S4 E7 E9 E8 E6 | S5 E5 E1 E2 | S6 E4 E2 E3 E5 E7

CORRELATED TRAINING SAMPLES (SEQUENCE PATTERNS)

S1 E1 E2 E3 E1 | S2 E4 E5 E2 E6 | S3 E7 E5 E2 E8
S4 E7 E9 E8 E6 | S5 E5 E1 E2 | S6 E4 E2 E3 E5 E7

S1 E1 E2 E3 E1 | S2 E4 E5 E2 E6 | S3 E7 E5 E2 E8
S4 E7 E9 E8 E6 | S5 E5 E1 E2 | S6 E4 E2 E3 E5 E7

S1 E1 E2 E3 E1 | S2 E4 E5 E2 E6 | S3 E7 E5 E2 E8
S4 E7 E9 E8 E6 | S5 E5 E1 E2 | S6 E4 E2 E3 E5 E7

REPETITION OF THE SAME ELEMENT IN THE SAME SEQUENCE

S1 E1 E2 E3 E1 | S2 E4 E5 E2 E6 | S3 E7 E5 E2 E8
S4 E7 E9 E8 E6 | S5 E5 E1 E2 | S6 E4 E2 E3 E5 E7

REPETITION OF THE SAME INITIAL CONTEXTS

S1 E1 E2 E3 E1 | S2 E4 E5 E2 E6 | S3 E7 E5 E2 E8
S4 E7 E9 E8 E6 | S5 E5 E1 E2 | S6 E4 E2 E3 E5 E7

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1 | 1x S2 E4 E5 E2 E6 | 1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6 | 1x S5 E5 E1 E2 | 1x S6 E4 E2 E3 E5 E7

ANAKG-2

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1

1x S2 E4 E5 E2 E6

1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6

1x S5 E5 E1 E2

1x S6 E4 E2 E3 E5 E7

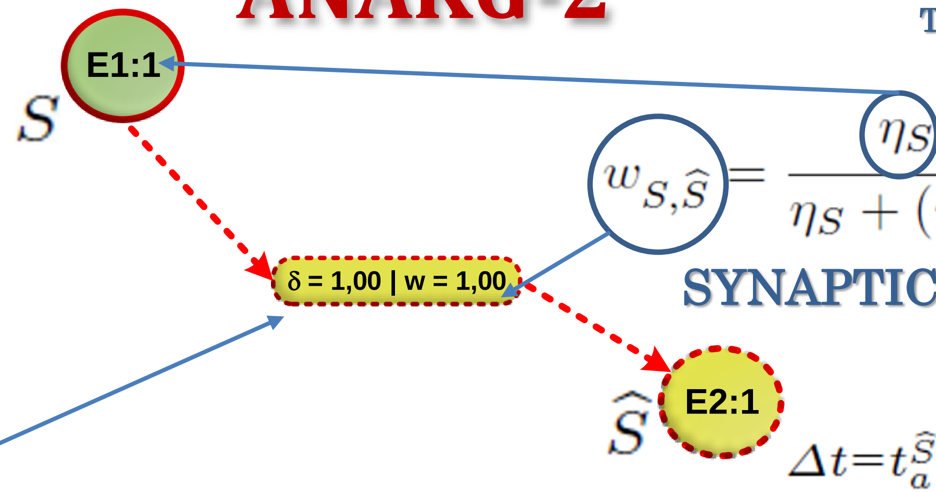
ANAKG-2

TRAINING SEQUENCES

1x	S1	E1	E2	E3	E1	
1x	S2	E4	E5	E2	E6	
1x	S3	E7	E5	E2	E8	
1x	S4	E7	E9	E8	E6	
1x	S5	E5	E1	E2		
1x	S6	E4	E2	E3	E5	E7

ANAKG-2

ACTIVATION THRESHOLD $\theta_{\widehat{S}} = 1$



$$w_{S,\widehat{S}} = \frac{\eta_S \cdot \delta_{S,\widehat{S}} \cdot \theta_{\widehat{S}}}{\eta_S + (\eta_S - 1) \cdot \delta_{S,\widehat{S}}}$$

SYNAPTIC WEIGHT

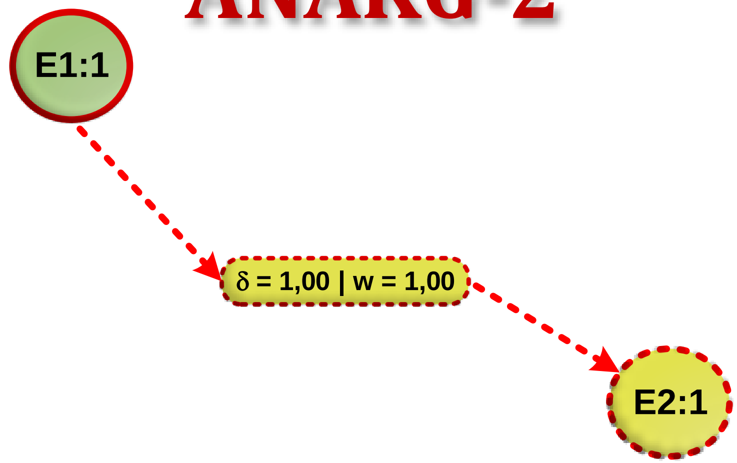
SYNAPTIC EFFICIENCY

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S}\ :\ (\cdots \rightsquigarrow S \rightsquigarrow \cdots \rightsquigarrow \widehat{S} \rightsquigarrow \ldots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t - t_a^{\widehat{S}}}{\omega}} \right)^{\gamma}$$

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7

ANAKG-2

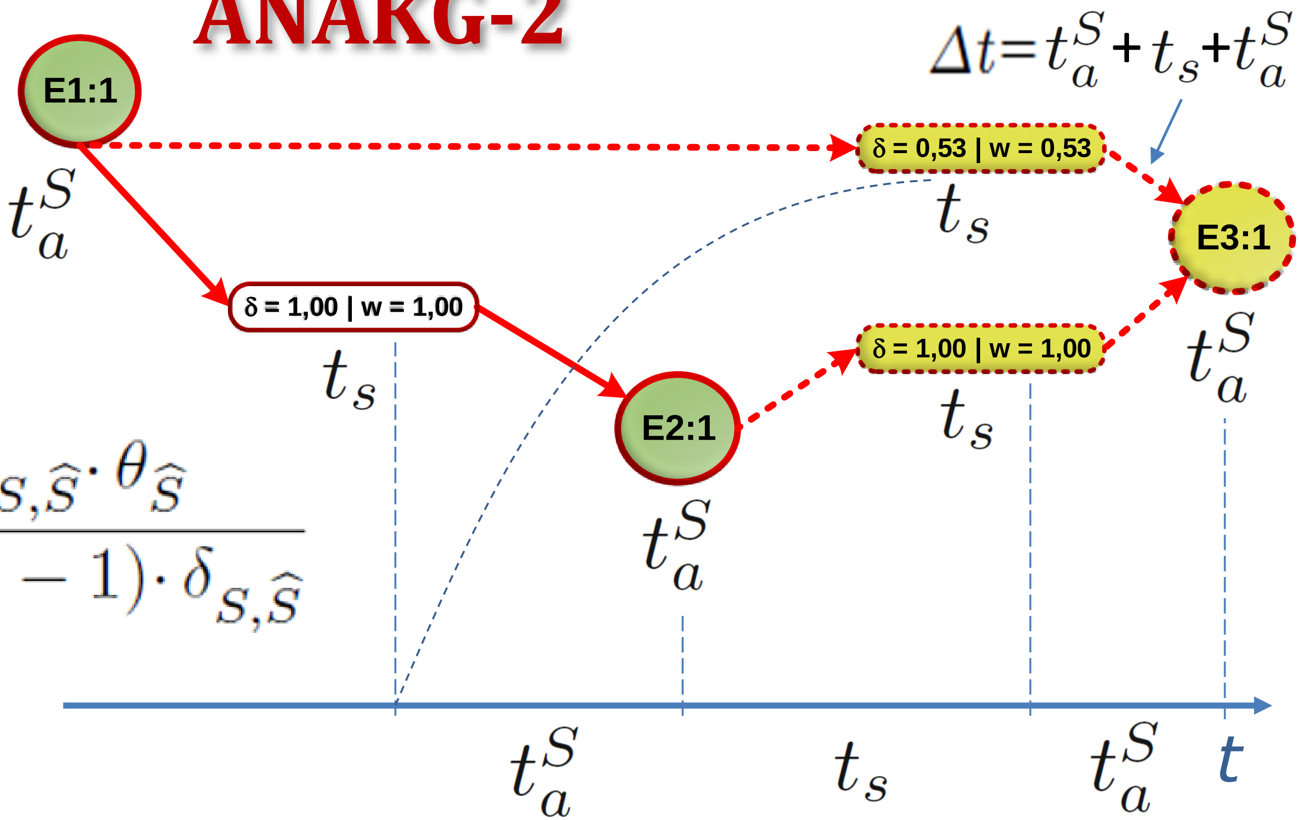


TRAINING SEQUENCES

1x S1 E1 E2 E3 E1 1x S2 E4 E5 E2 E6 1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6 1x S5 E5 E1 E2 1x S6 E4 E2 E3 E5 E7

ANAKG-2



SYNAPTIC WEIGHT

$$w_{S,\widehat{S}} = \frac{\eta_S \cdot \delta_{S,\widehat{S}} \cdot \theta_{\widehat{S}}}{\eta_S + (\eta_S - 1) \cdot \delta_{S,\widehat{S}}}$$

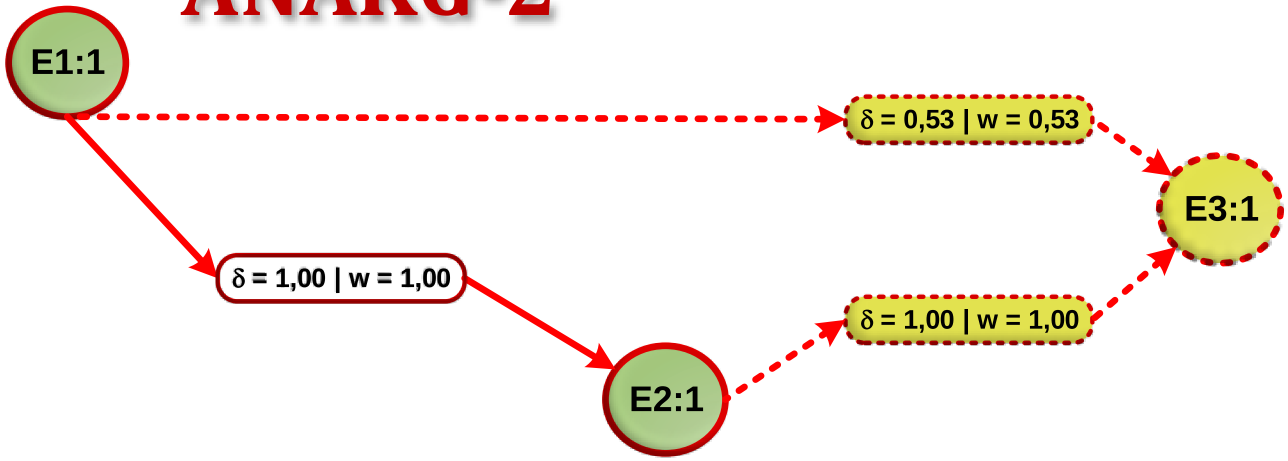
SYNAPTIC EFFICIENCY

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S} \,:\, (\cdots \rightsquigarrow S \rightsquigarrow \cdots \rightsquigarrow \widehat{S} \rightsquigarrow \ldots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t - t_a^{\widehat{S}}}{\omega}} \right)^{\gamma}$$

TRAINING SEQUENCES

1x	S1	E1	E2	E3	E1	
1x	S2	E4	E5	E2	E6	
1x	S3	E7	E5	E2	E8	
1x	S4	E7	E9	E8	E6	
1x	S5	E5	E1	E2		
1x	S6	E4	E2	E3	E5	E7

ANAKG-2



TRAINING SEQUENCES

1x S1 E1 E2 E3 E1

1x S2 E4 E5 E2 E6

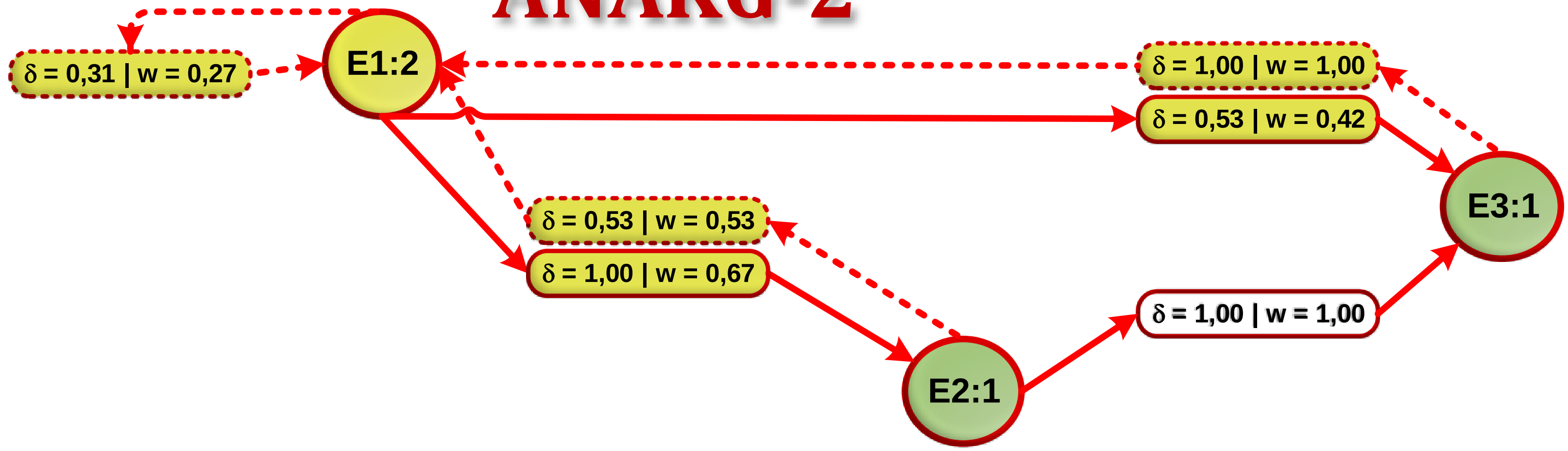
1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6

1x S5 E5 E1 E2

1x S6 E4 E2 E3 E5 E7

ANAKG-2



TRAINING SEQUENCES

1x S1 E1 E2 E3 E1

1x S2 E4 E5 E2 E6

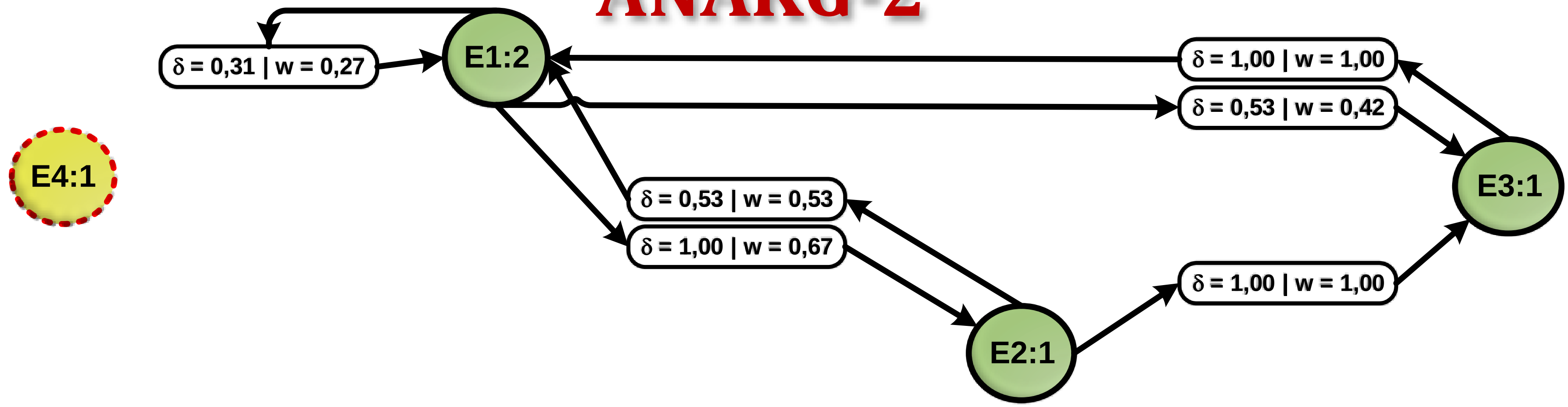
1x S3 E7 E5 E2 E8

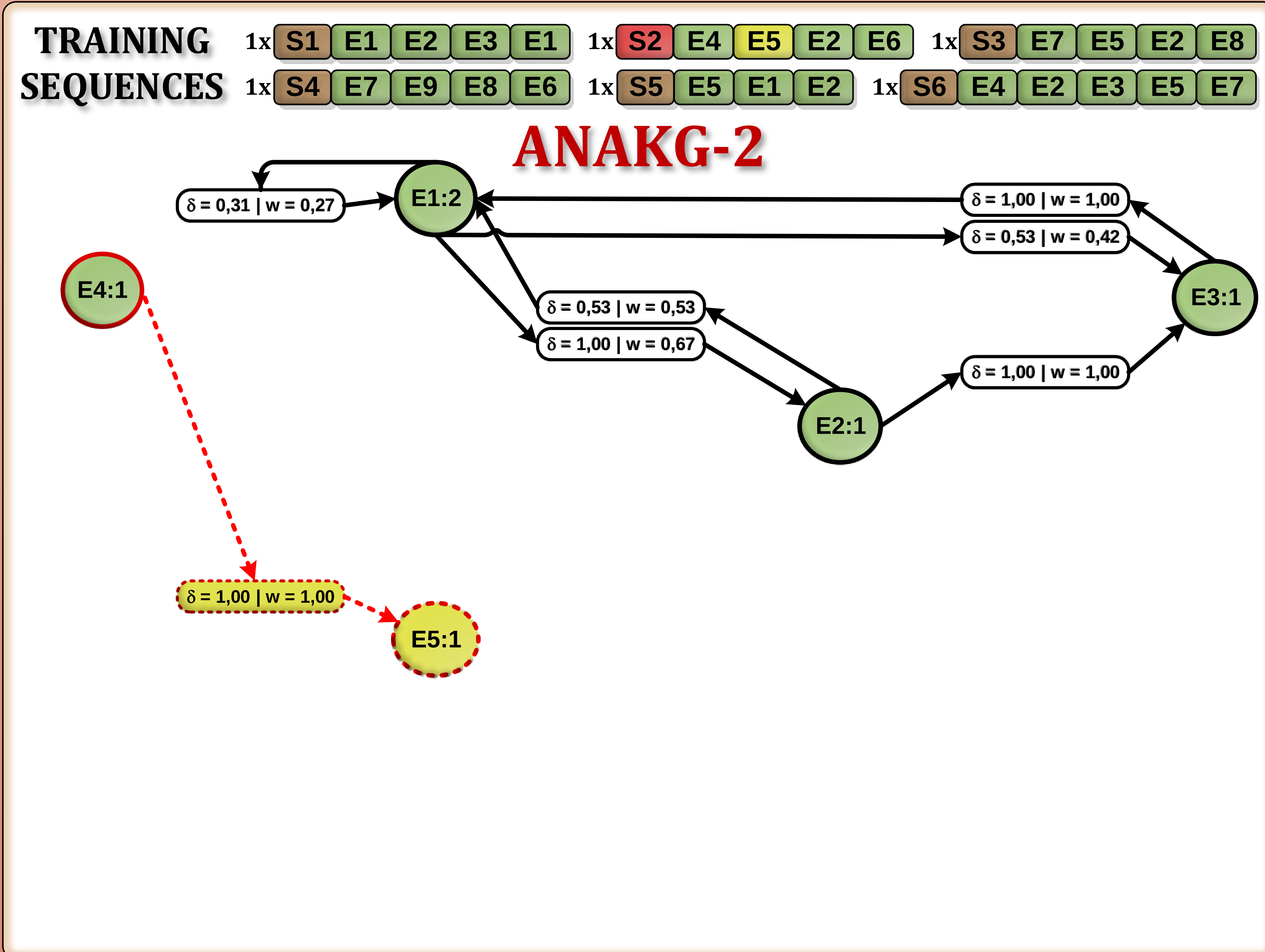
1x S4 E7 E9 E8 E6

1x S5 E5 E1 E2

1x S6 E4 E2 E3 E5 E7

ANAKG-2



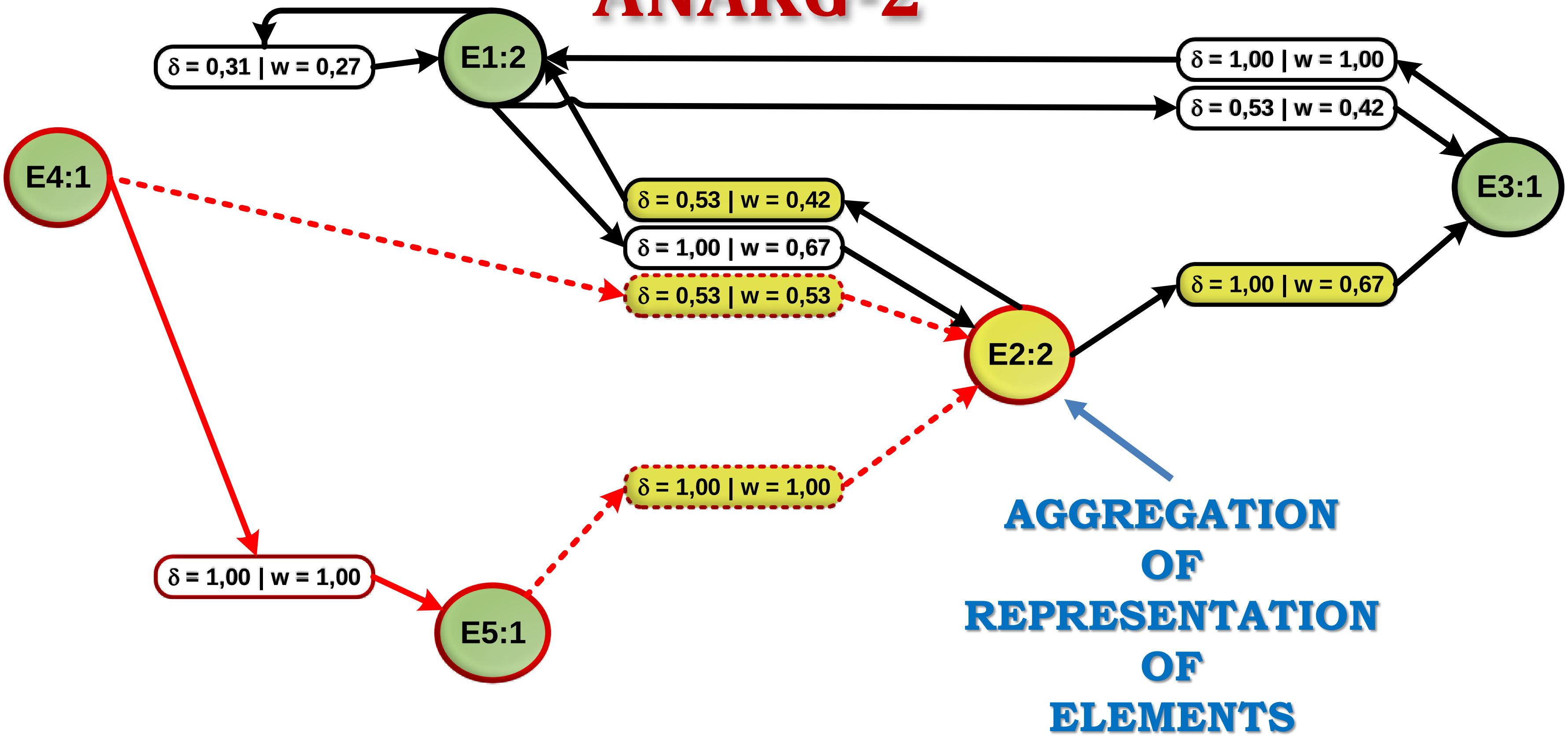

TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
δ = 0,31 | w = 0,27
E1:2
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42
E4:1
E3:1
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,67
δ = 1,00 | w = 1,00
E2:1
δ = 1,00 | w = 1,00
E5:1

TRAINING SEQUENCES

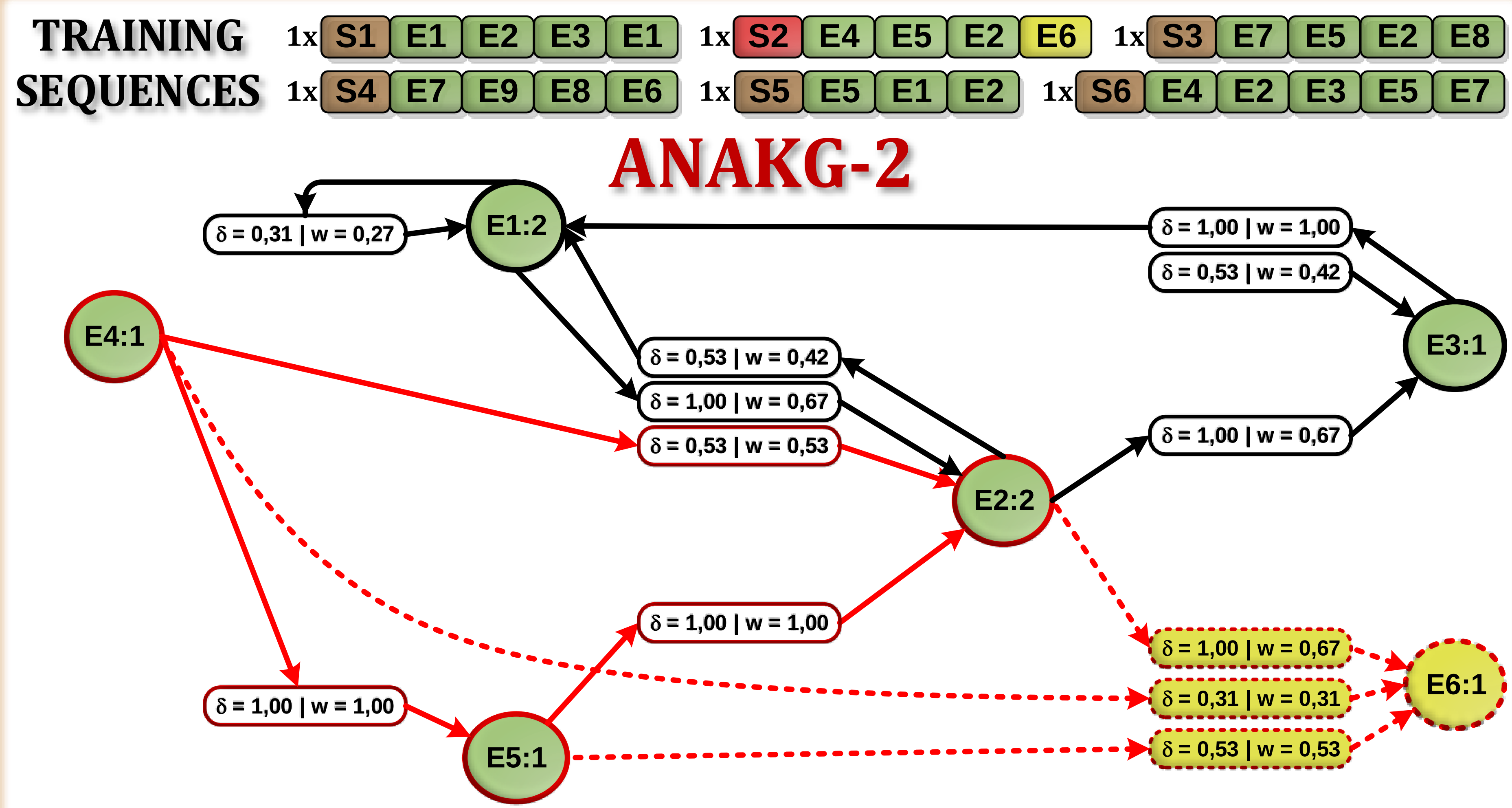
1x S1 E1 E2 E3 E1 — 1x S2 E4 E5 E2 E6 — 1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6 — 1x S5 E5 E1 E2 — 1x S6 E4 E2 E3 E5 E7

ANAKG-2



CONSOLIDATION OF REPRESENTATION OF SEQUENCES


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:2
E2:2
E3:1
E4:1
E5:1
E6:1
δ = 0,31 | w = 0,27
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,67
δ = 1,00 | w = 1,00
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 0,31 | w = 0,31
δ = 0,53 | w = 0,53

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1

1x S2 E4 E5 E2 E6

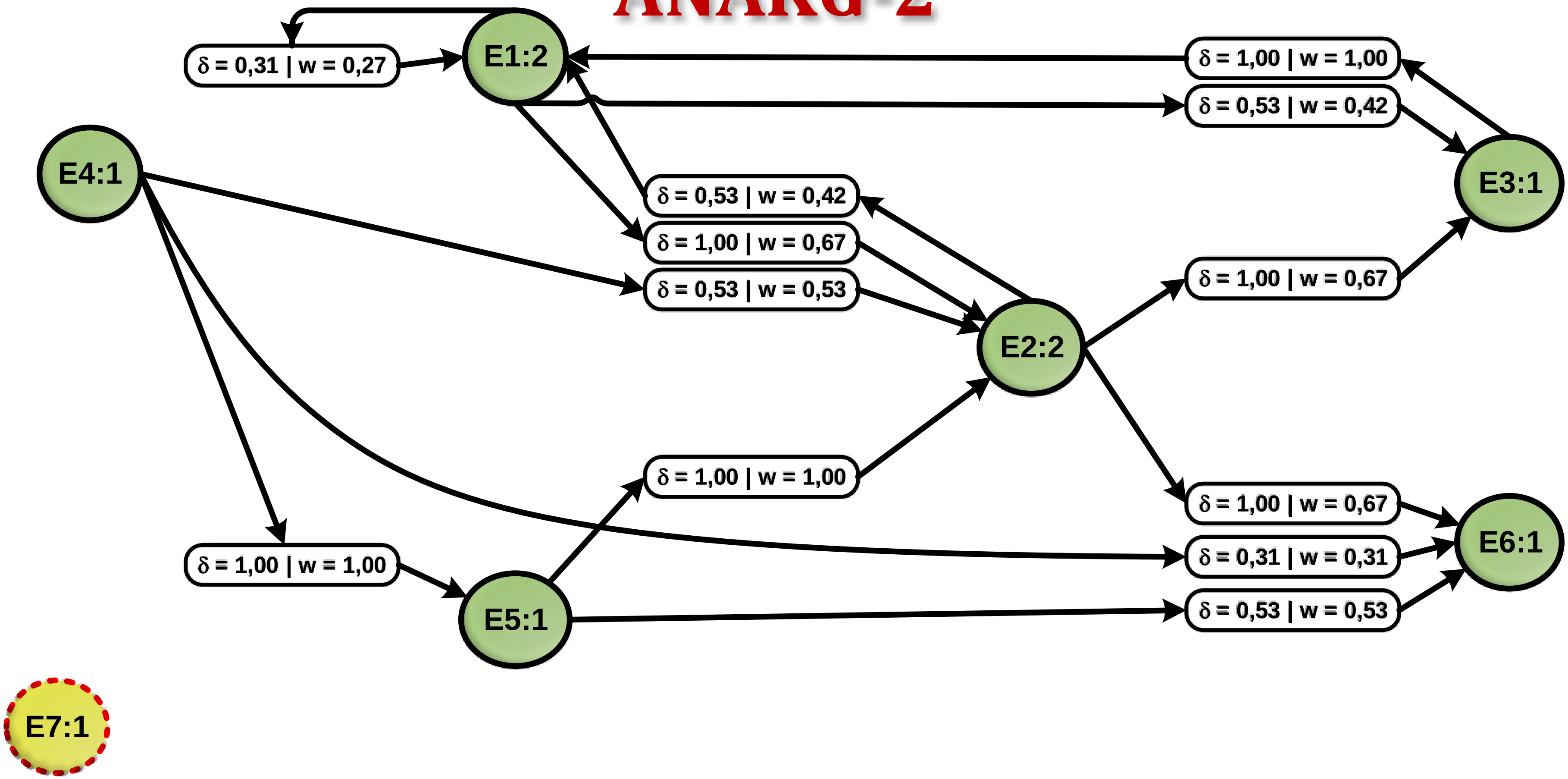
1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6

1x S5 E5 E1 E2

1x S6 E4 E2 E3 E5 E7

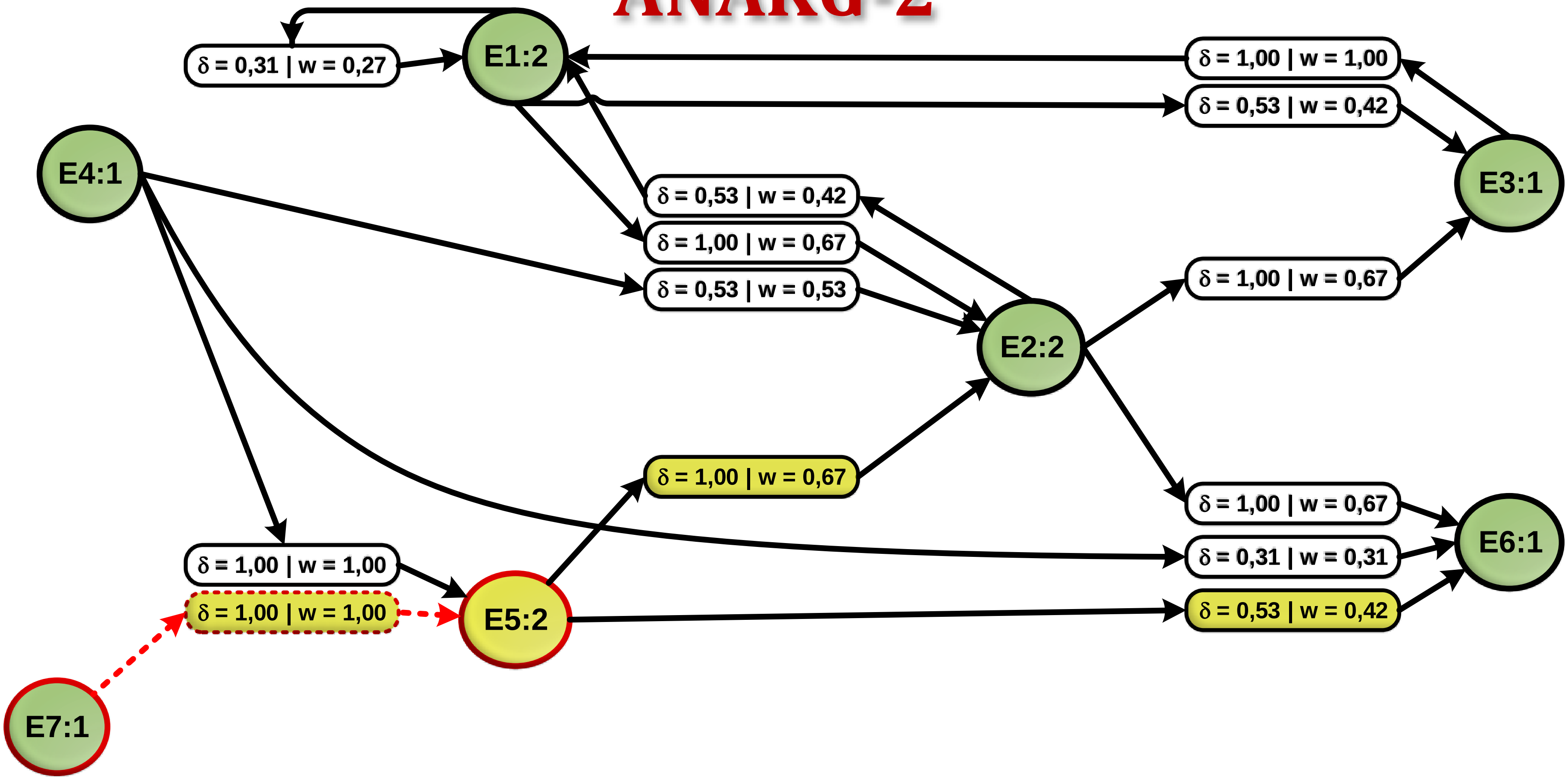
ANAKG-2

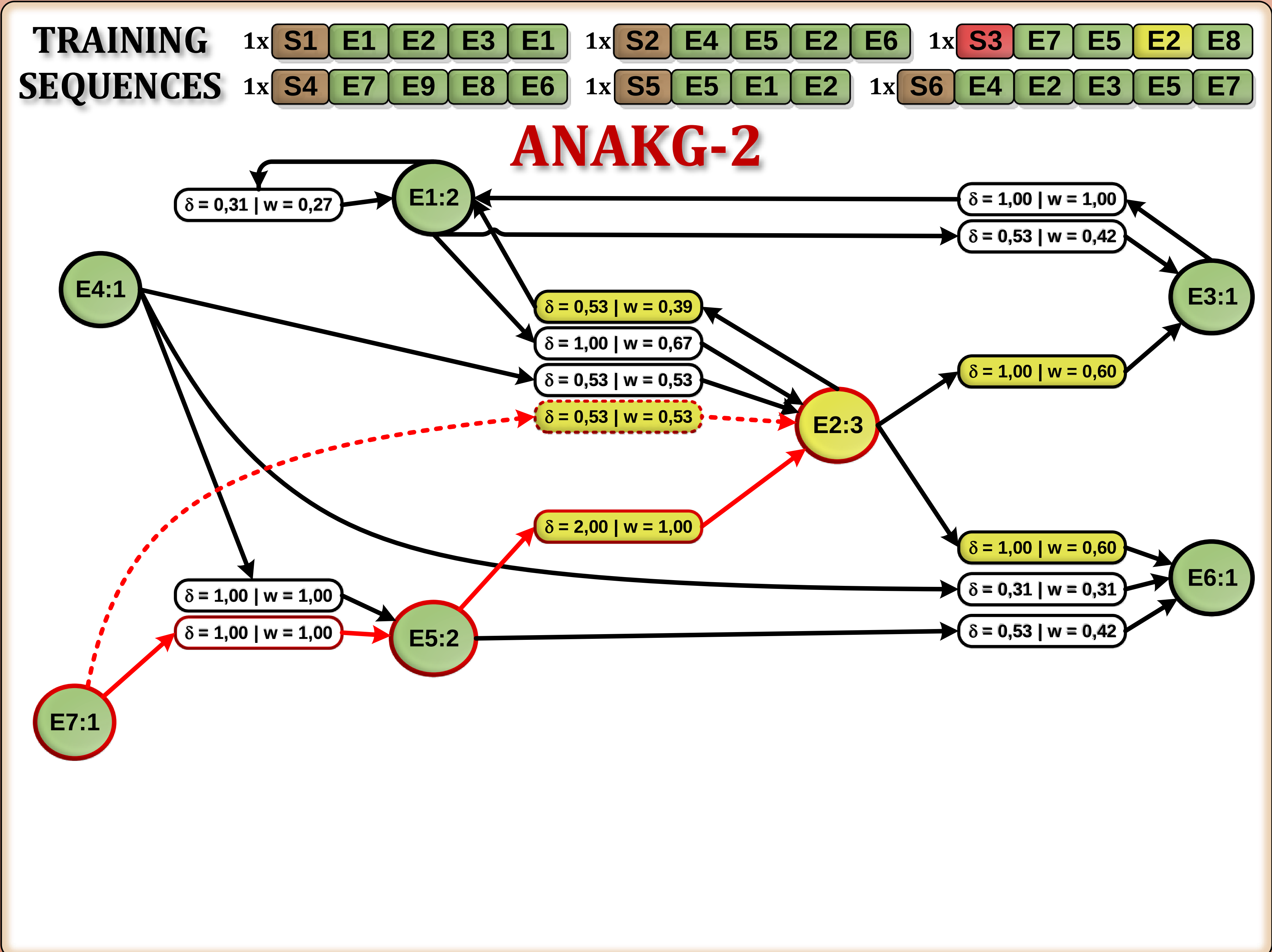


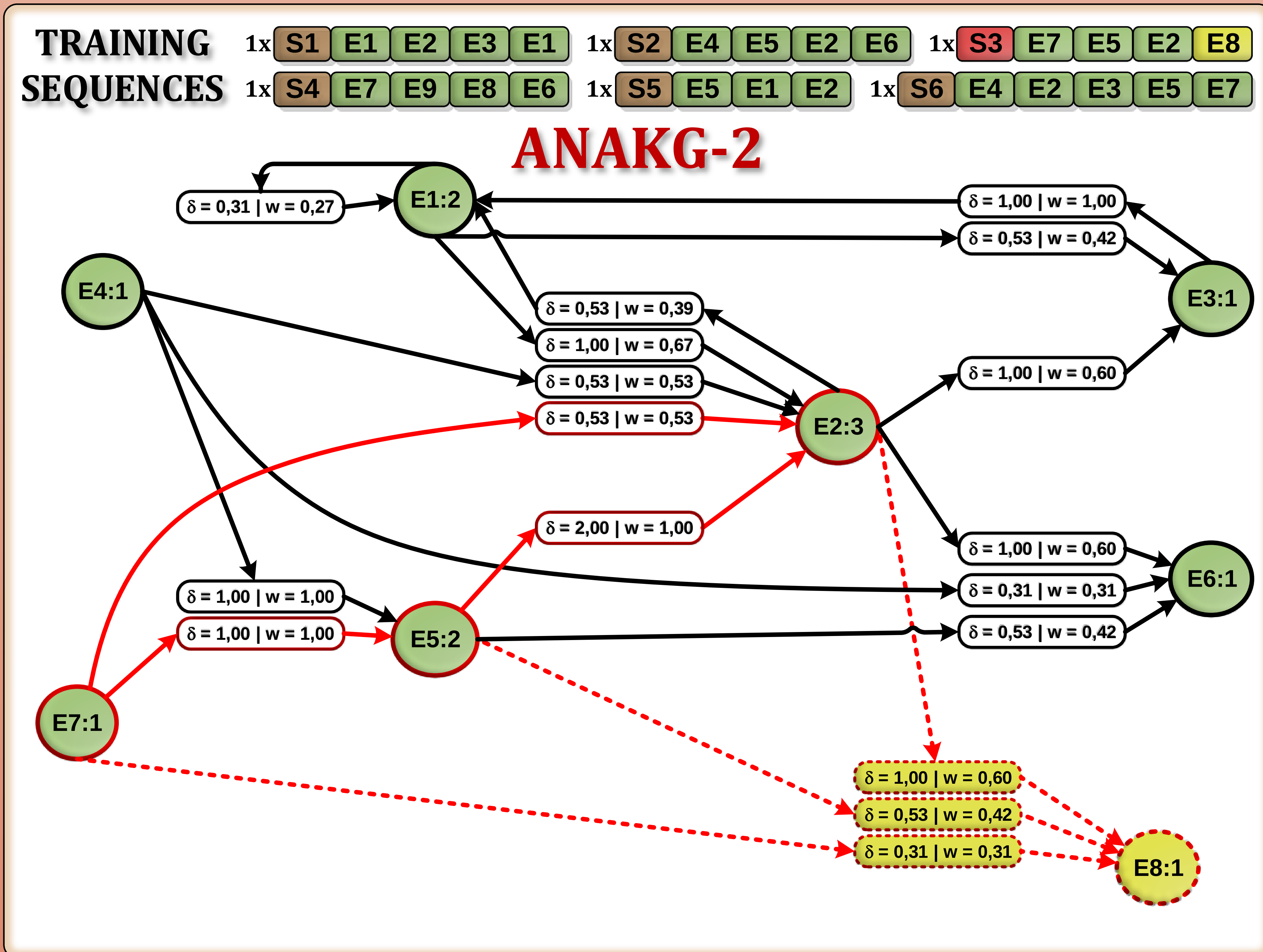
TRAINING SEQUENCES

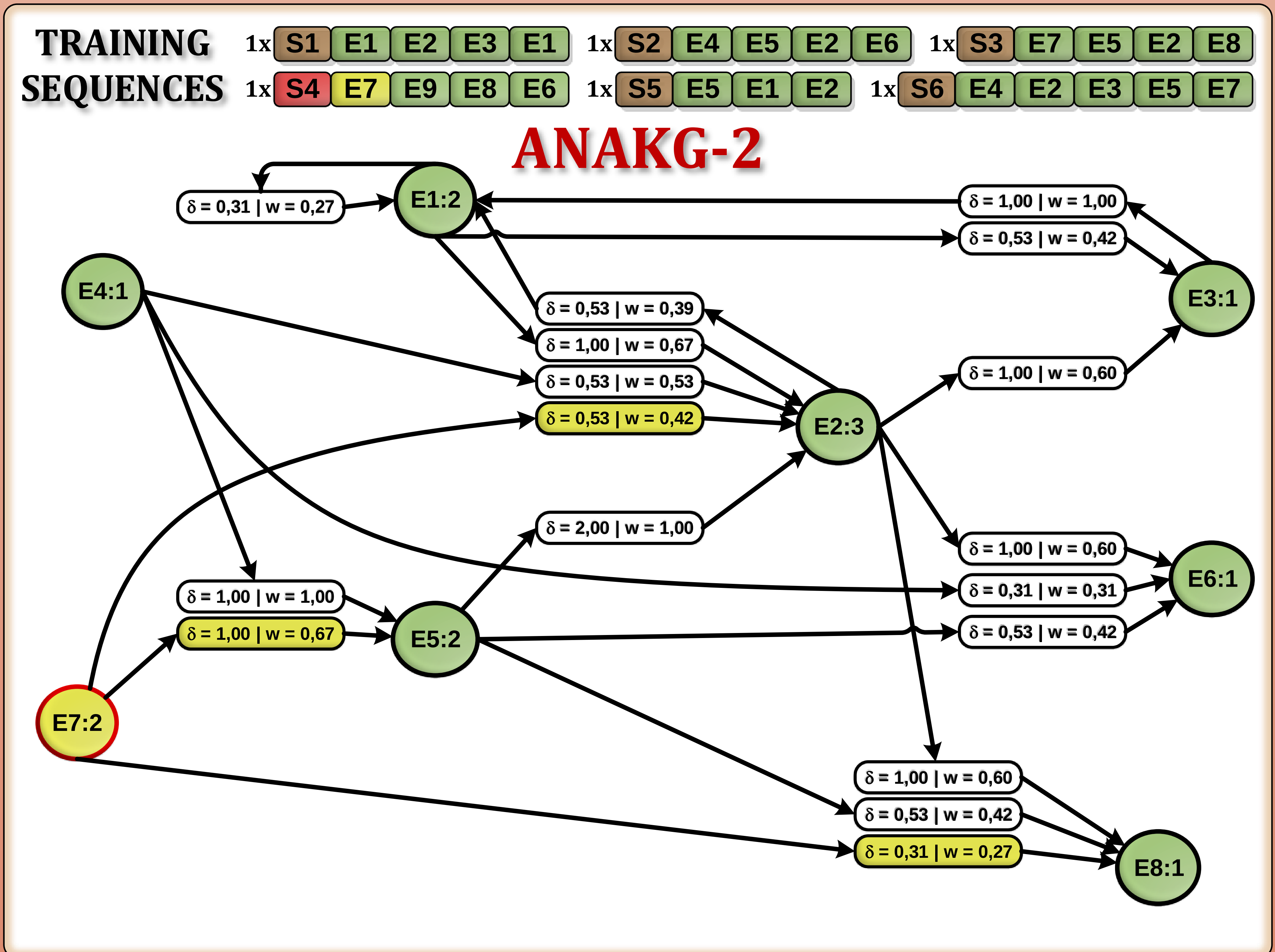
1x	S1	E1	E2	E3	E1
1x	S2	E4	E5	E2	E6
1x	S3	E7	E5	E2	E8
1x	S4	E7	E9	E8	E6
1x	S5	E5	E1	E2	
1x	S6	E4	E2	E3	E5	E7

ANAKG-2




TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:2
E2:3
E3:1
E4:1
E5:2
E6:1
E7:1
δ = 0,31 | w = 0,27
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,39
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,53
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,60
δ = 2,00 | w = 1,00
δ = 1,00 | w = 0,60
δ = 1,00 | w = 1,00
δ = 0,31 | w = 0,31
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:2
E2:3
E3:1
E4:1
E5:2
E6:1
E7:1
E8:1
δ = 0,31 | w = 0,27
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,39
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,53
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,60
δ = 2,00 | w = 1,00
δ = 1,00 | w = 0,60
δ = 0,31 | w = 0,31
δ = 0,53 | w = 0,42
δ = 1,00 | w = 1,00
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,60
δ = 0,53 | w = 0,42
δ = 0,31 | w = 0,31



TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:2
E2:3
E3:1
E4:1
E5:2
E6:1
E7:2
E8:1
δ = 0,31 | w = 0,27
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,39
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,53
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,60
δ = 2,00 | w = 1,00
δ = 1,00 | w = 0,60
δ = 0,31 | w = 0,31
δ = 0,53 | w = 0,42
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60
δ = 0,53 | w = 0,42
δ = 0,31 | w = 0,27

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1

1x S2 E4 E5 E2 E6

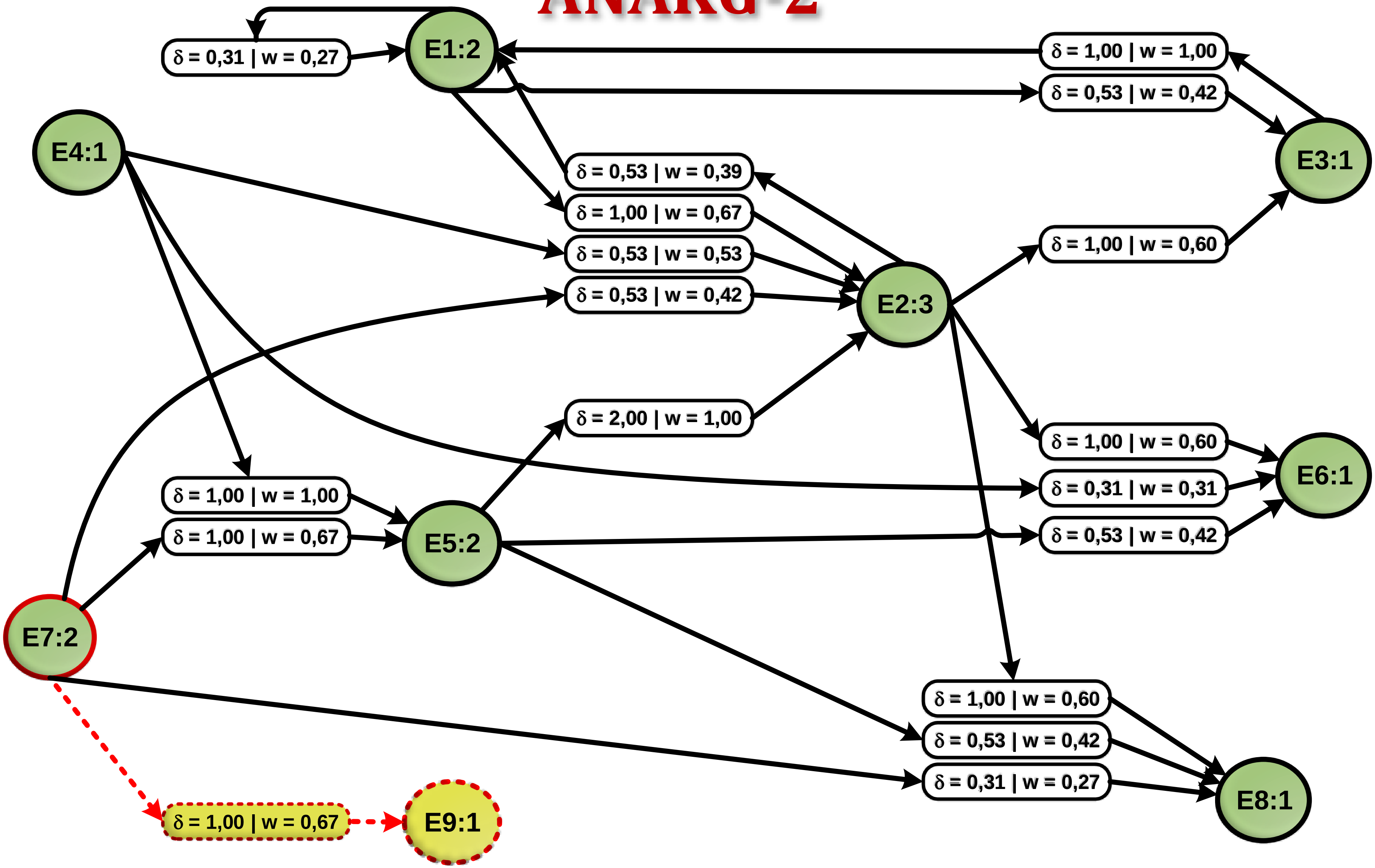
1x S3 E7 E5 E2 E8

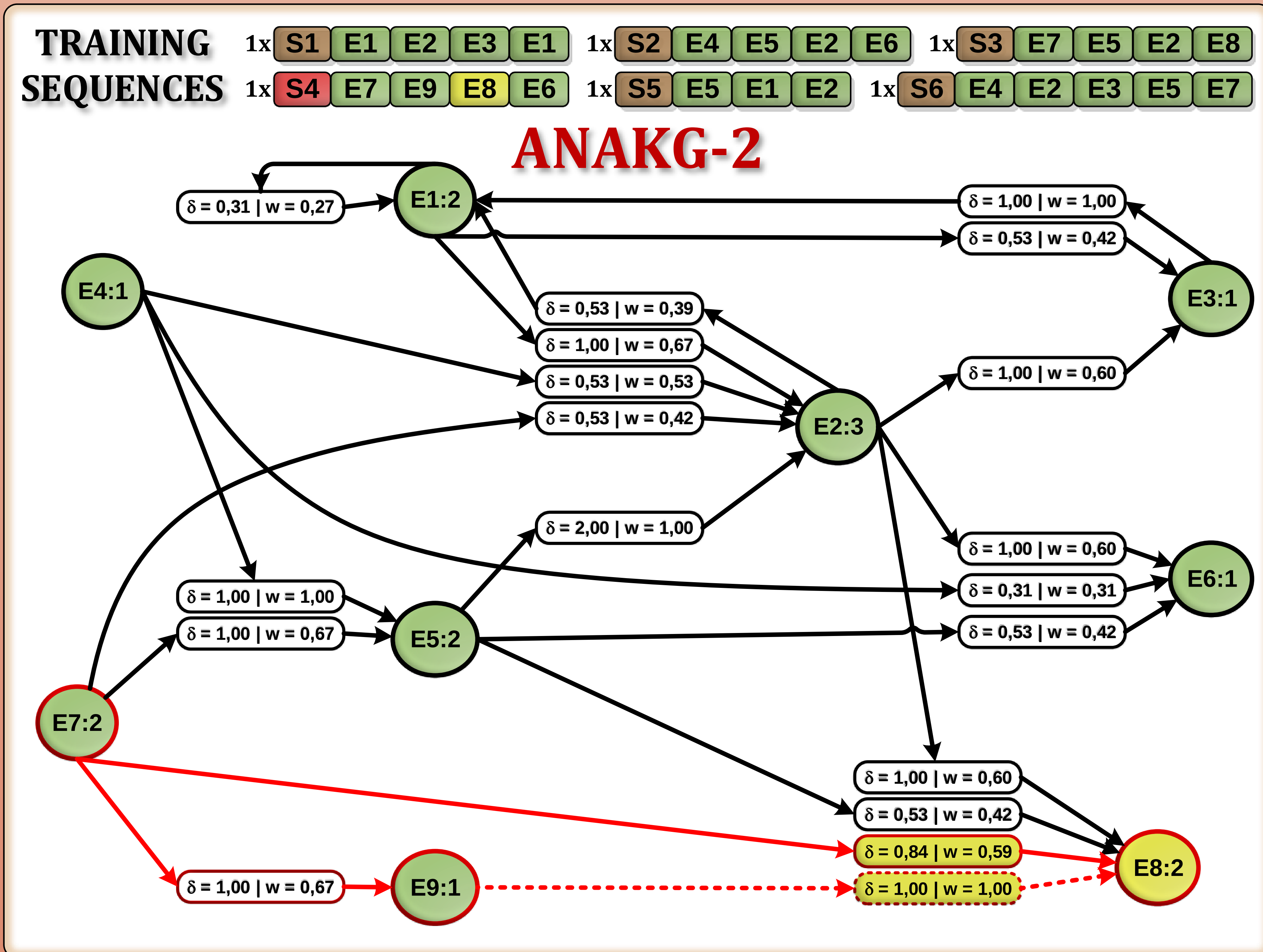
1x S4 E7 E9 E8 E6

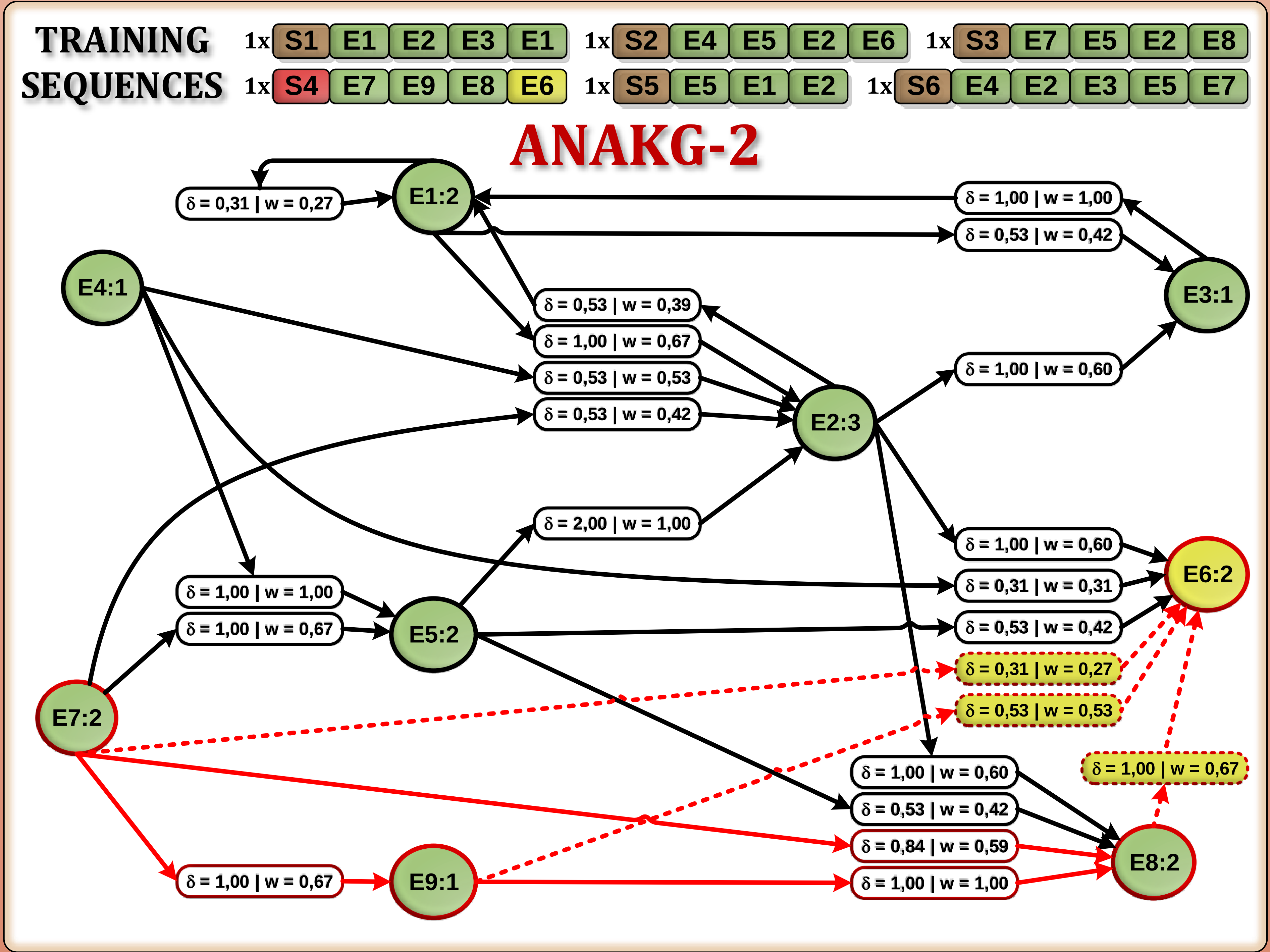
1x S5 E5 E1 E2

1x S6 E4 E2 E3 E5 E7

ANAKG-2




TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
δ = 0,31 | w = 0,27
E1:2
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42
E4:1
E3:1
δ = 0,53 | w = 0,39
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,53
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,60
E2:3
δ = 2,00 | w = 1,00
δ = 1,00 | w = 0,60
δ = 0,31 | w = 0,31
δ = 0,53 | w = 0,42
E6:1
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
E5:2
E7:2
δ = 1,00 | w = 0,60
δ = 0,53 | w = 0,42
δ = 0,84 | w = 0,59
δ = 1,00 | w = 1,00
E8:2
δ = 1,00 | w = 0,67
E9:1

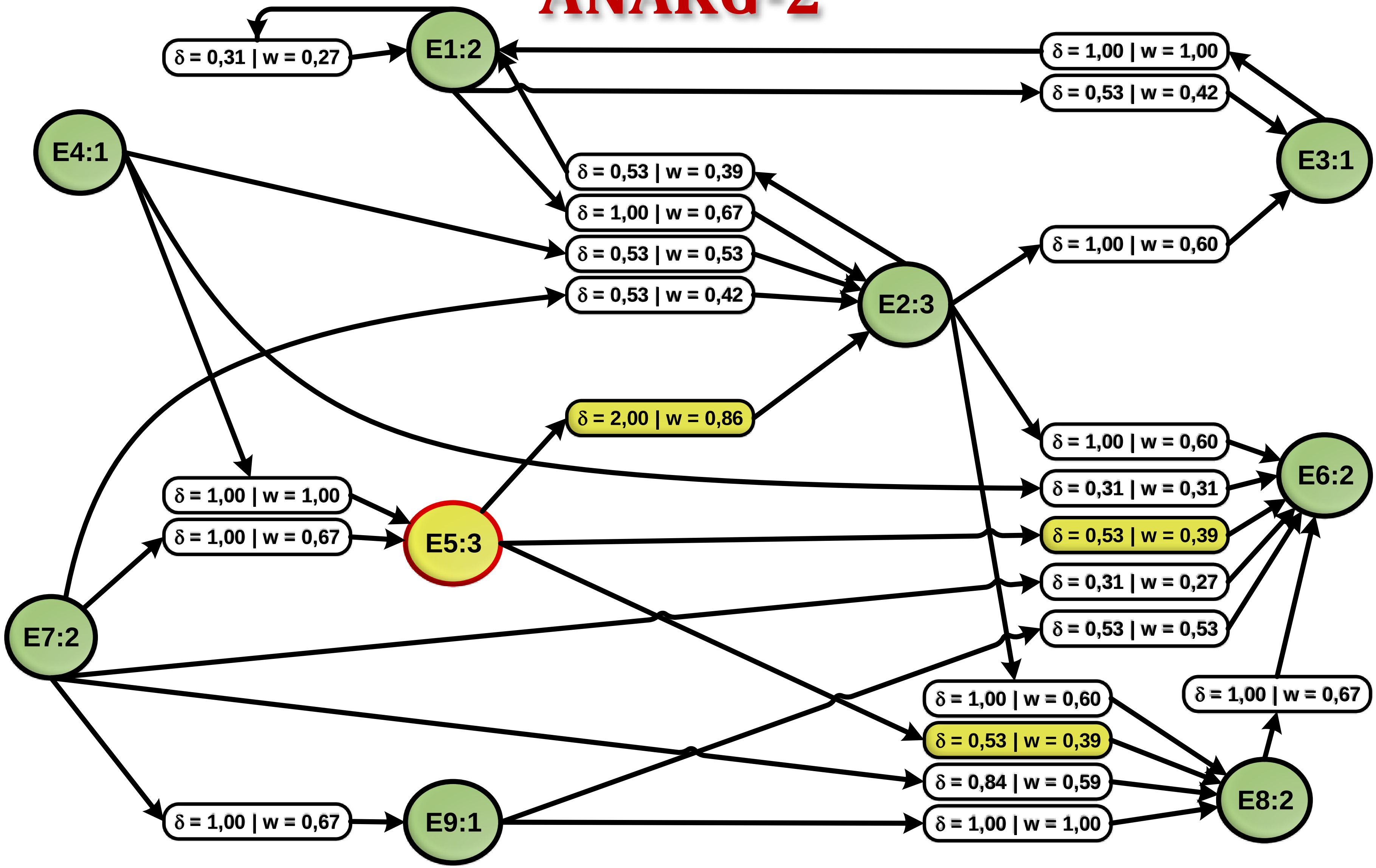


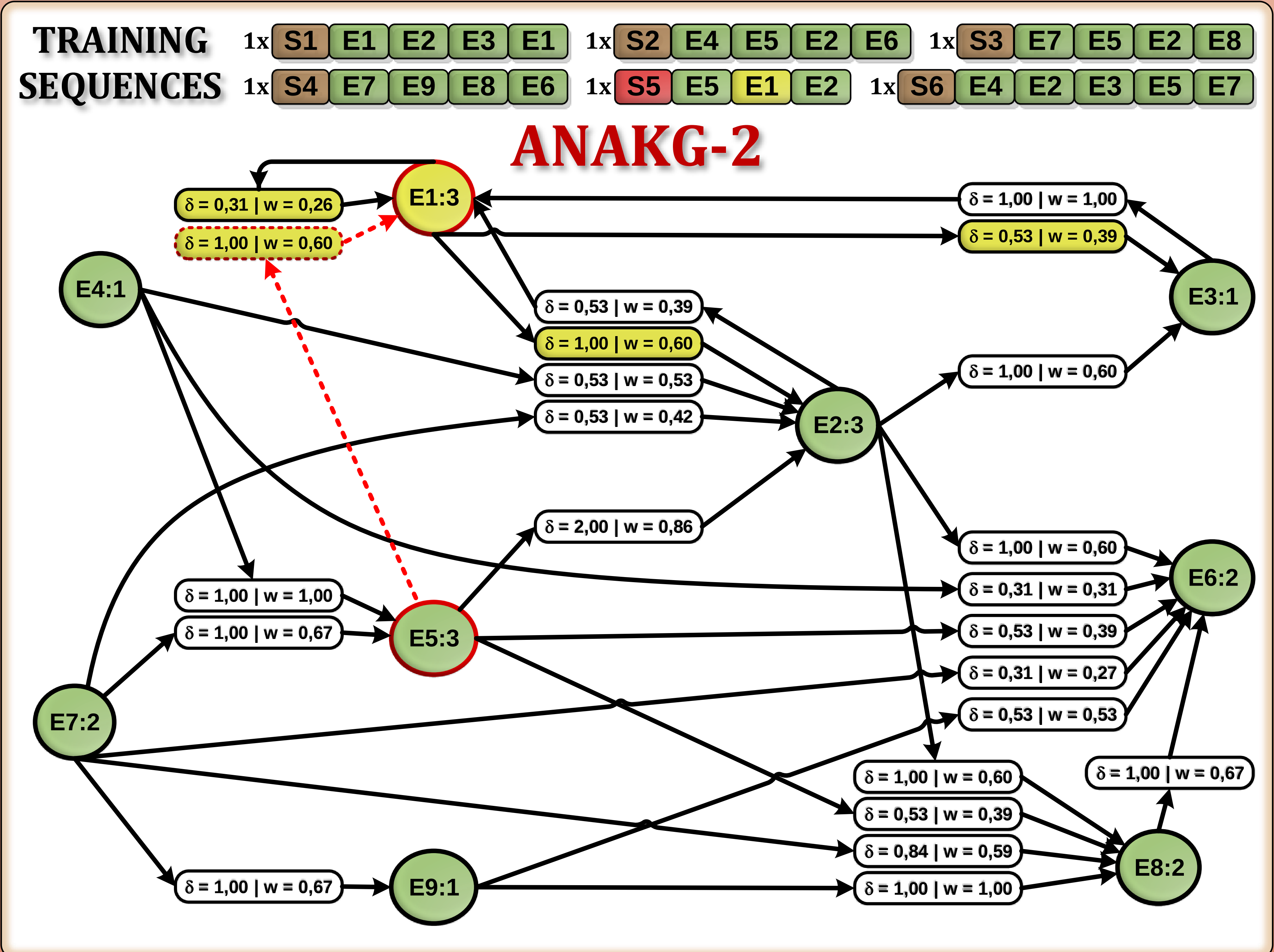
TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:2
E2:3
E3:1
E4:1
E5:2
E6:2
E7:2
E8:2
E9:1
δ = 0,31 | w = 0,27
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,39
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,53
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,60
δ = 2,00 | w = 1,00
δ = 1,00 | w = 0,60
δ = 0,31 | w = 0,31
δ = 0,53 | w = 0,42
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,53
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60
δ = 0,53 | w = 0,42
δ = 0,84 | w = 0,59
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,67

TRAINING SEQUENCES

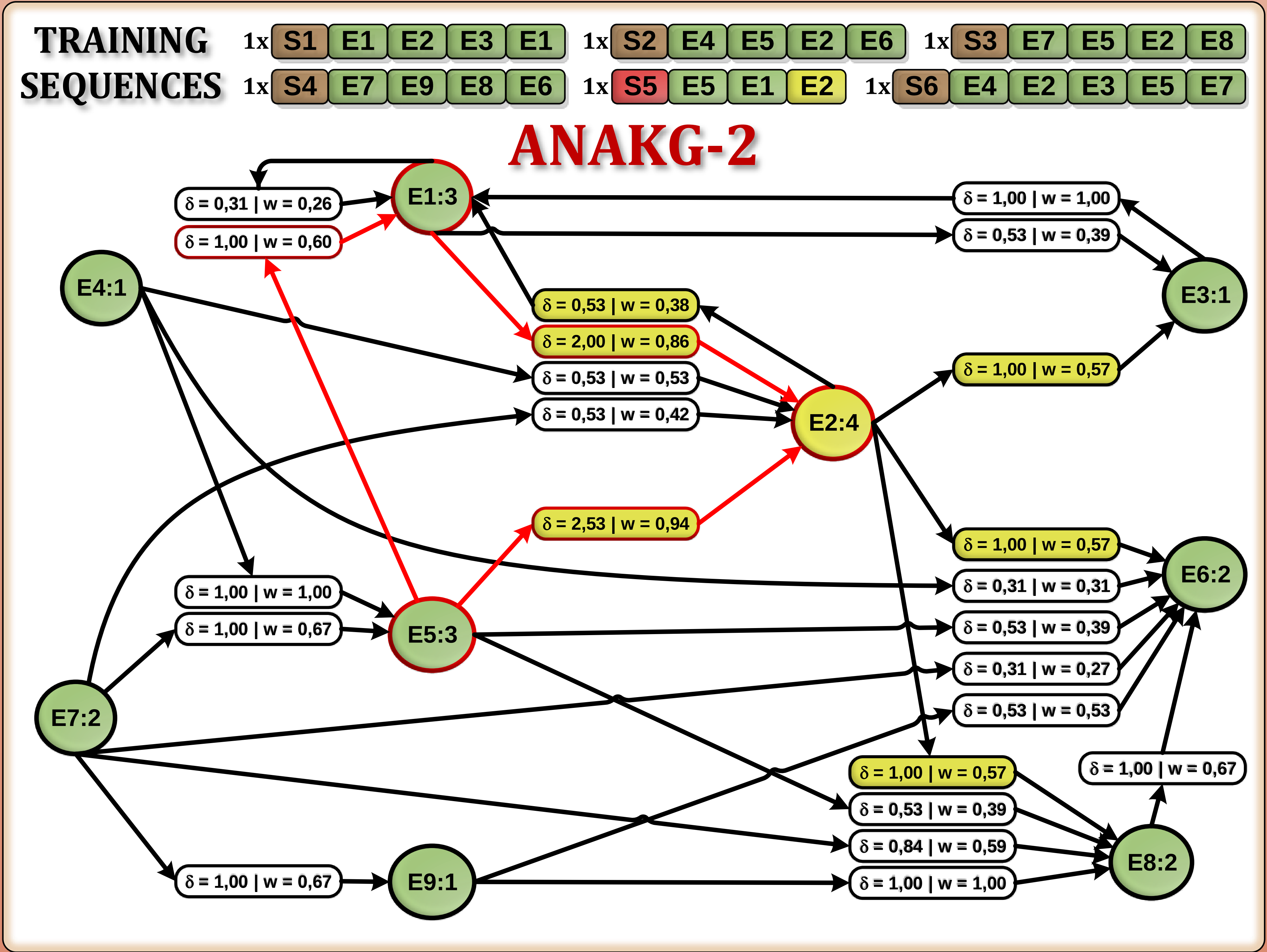
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7

ANAKG-2





TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:3
E2:3
E3:1
E4:1
E5:3
E6:2
E7:2
E8:2
E9:1
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,60
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,39
δ = 1,00 | w = 0,60
δ = 0,53 | w = 0,53
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,60
δ = 2,00 | w = 0,86
δ = 1,00 | w = 0,60
δ = 0,31 | w = 0,31
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,53
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60
δ = 0,53 | w = 0,39
δ = 0,84 | w = 0,59
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67



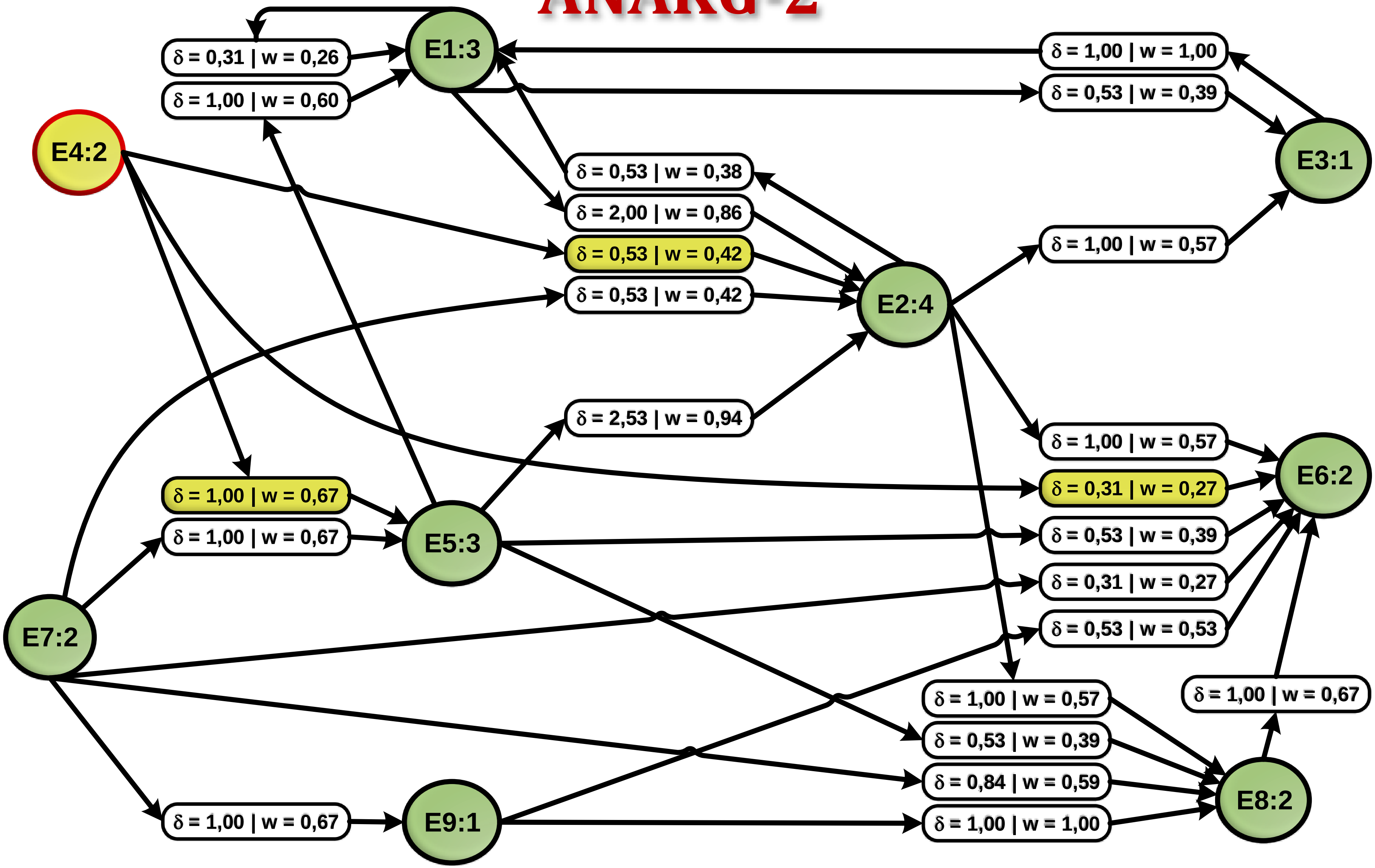
TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:3
E2:4
E3:1
E4:1
E5:3
E6:2
E7:2
E8:2
E9:1
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,60
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,38
δ = 2,00 | w = 0,86
δ = 0,53 | w = 0,53
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,57
δ = 2,53 | w = 0,94
δ = 1,00 | w = 0,57
δ = 0,31 | w = 0,31
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,53
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,57
δ = 0,53 | w = 0,39
δ = 0,84 | w = 0,59
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,67

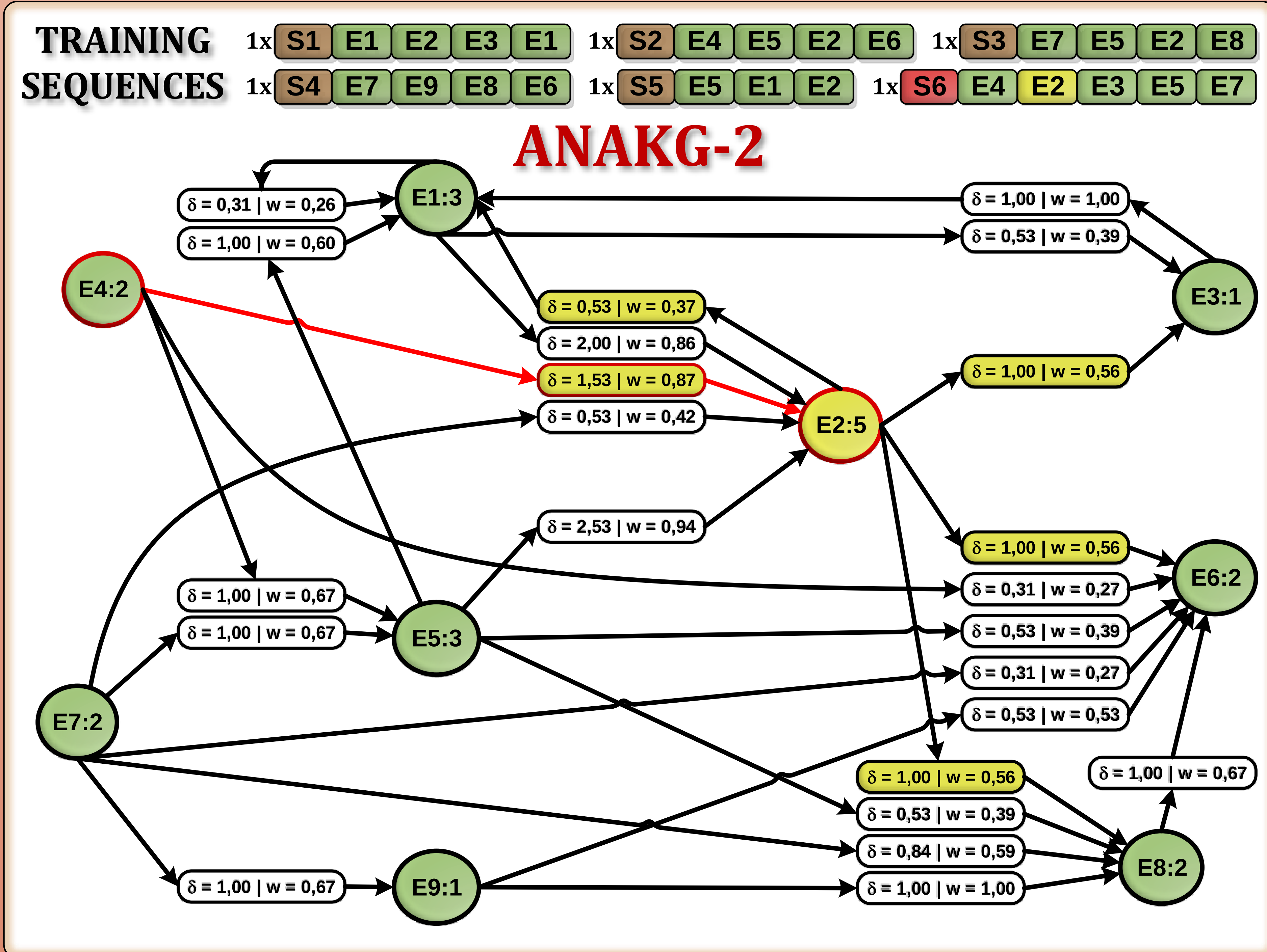
TRAINING SEQUENCES

1x S1 E1 E2 E3 E1 | 1x S2 E4 E5 E2 E6 | 1x S3 E7 E5 E2 E8

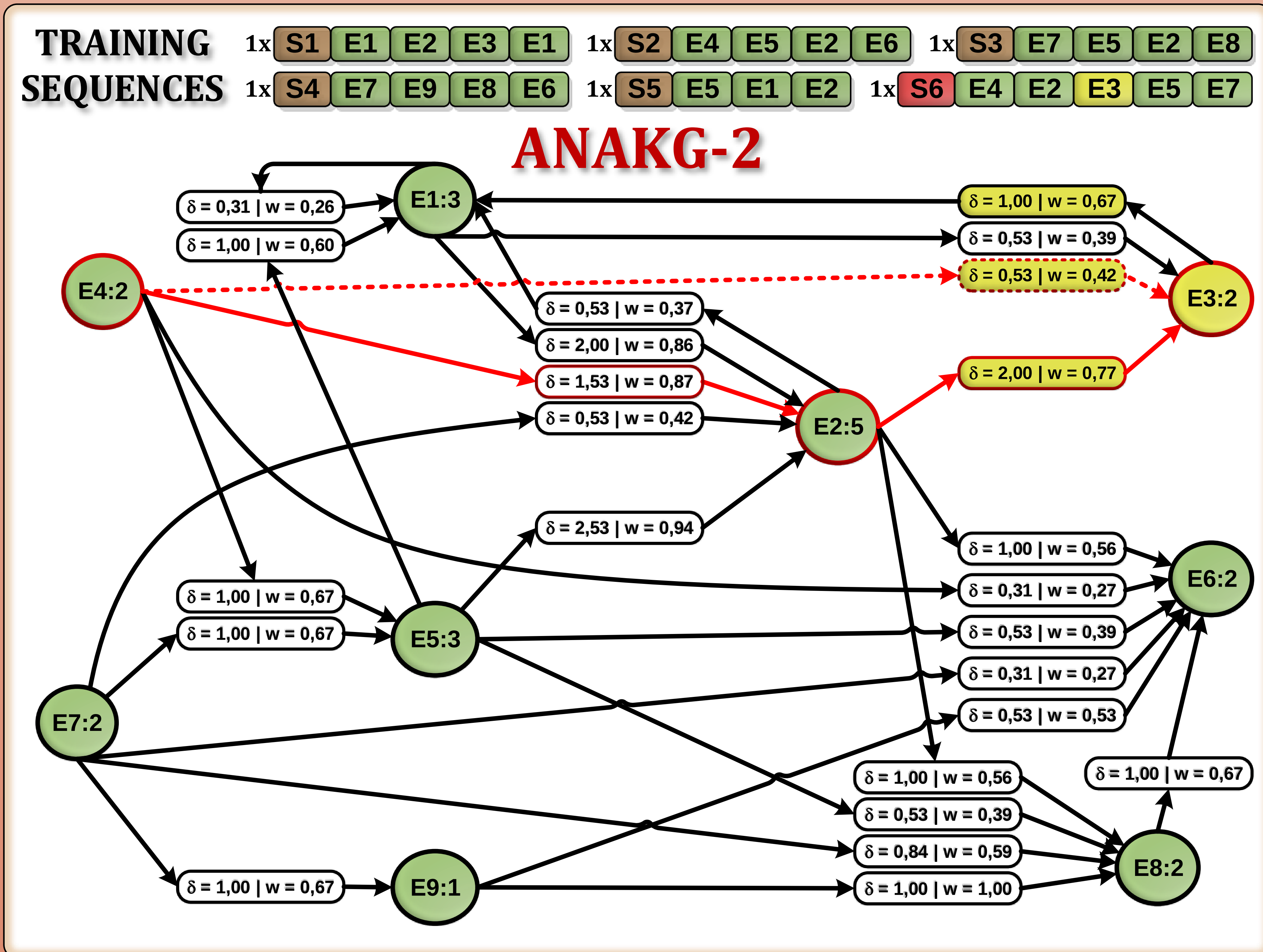
1x S4 E7 E9 E8 E6 | 1x S5 E5 E1 E2 | 1x S6 E4 E2 E3 E5 E7

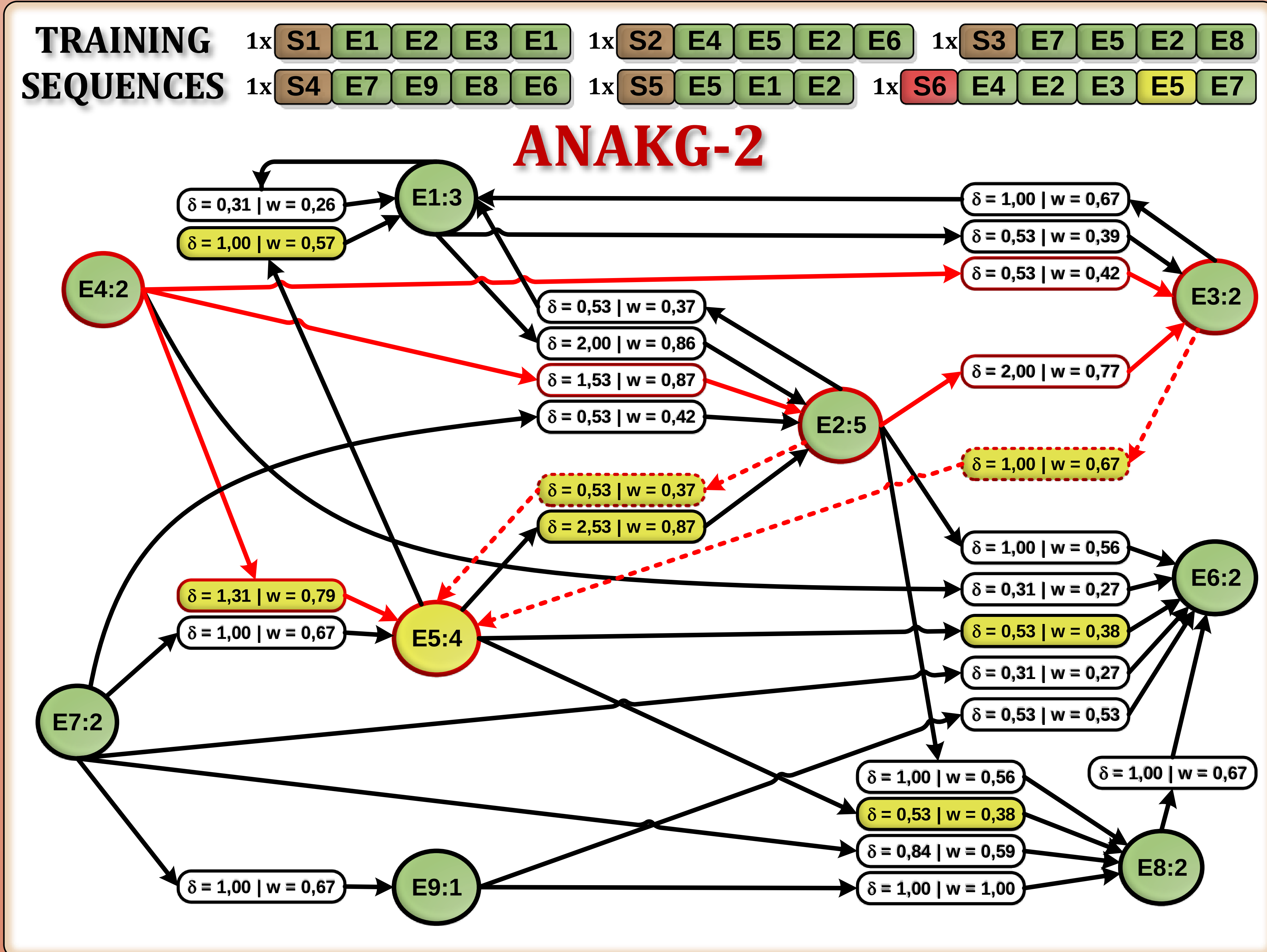
ANAKG-2

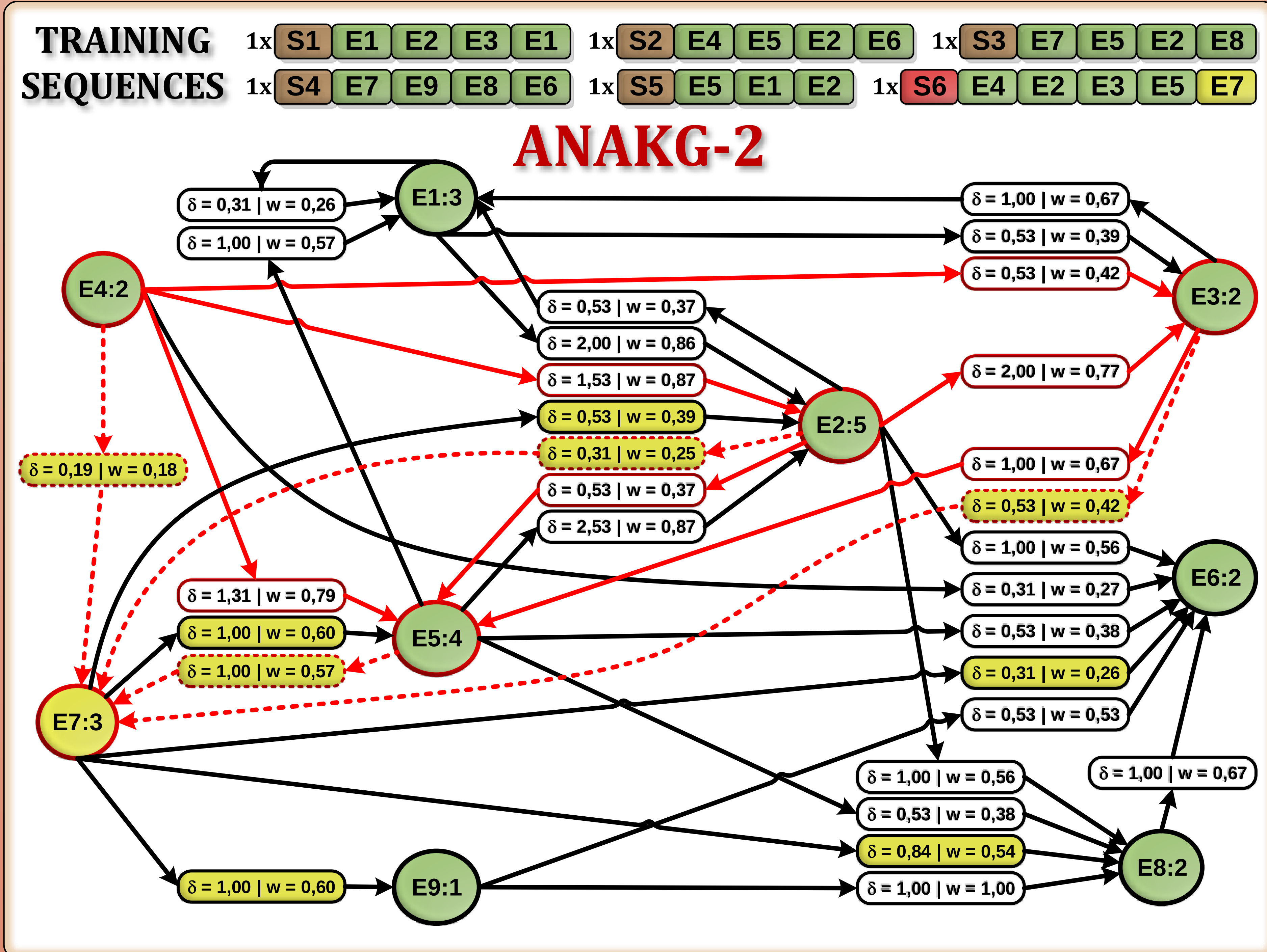


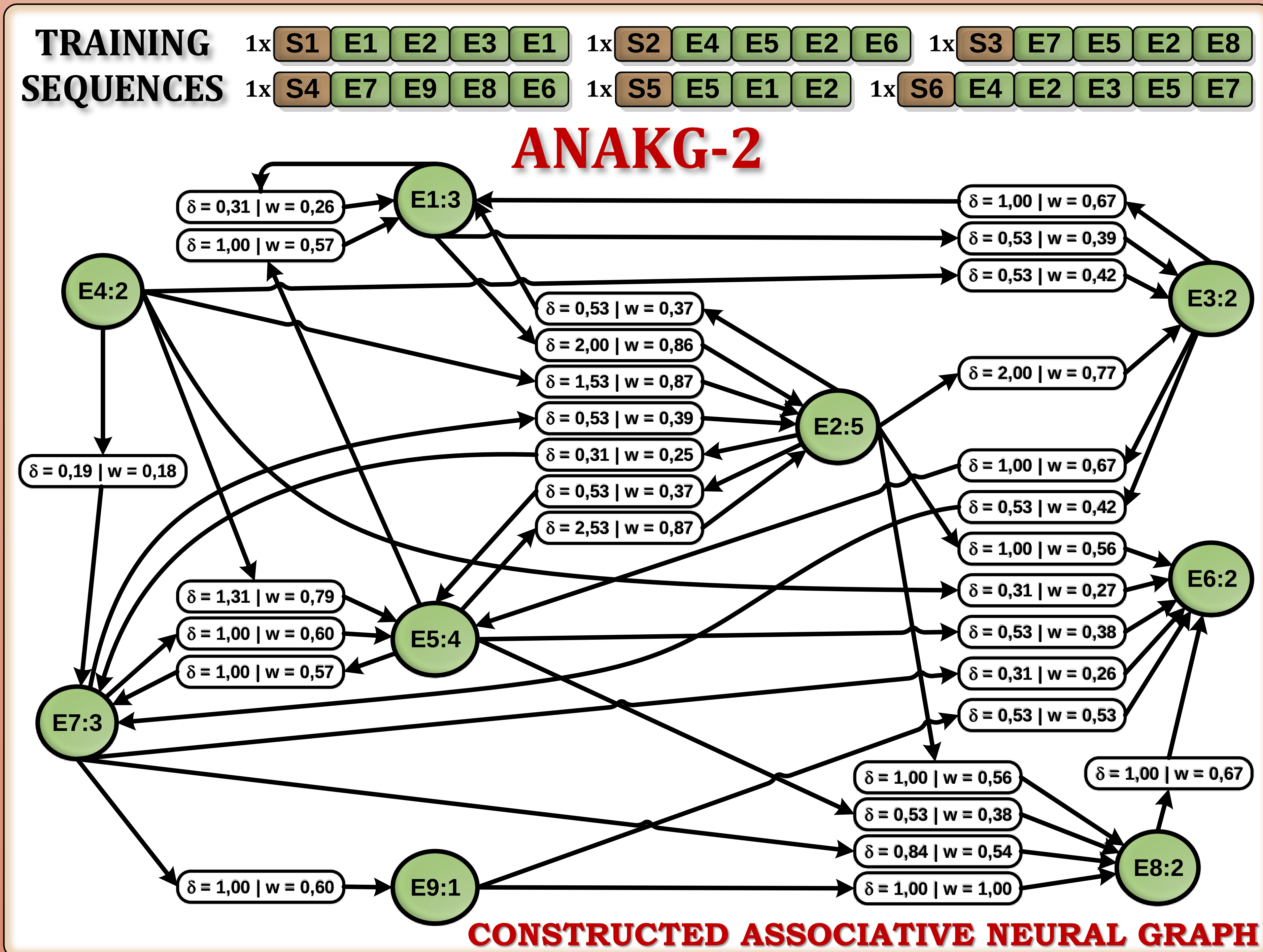


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:3
E2:5
E3:1
E4:2
E5:3
E6:2
E7:2
E8:2
E9:1
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,60
δ = 1,00 | w = 1,00
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 2,53 | w = 0,94
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,39
δ = 0,84 | w = 0,59
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:3
E2:5
E3:2
E4:2
E5:3
E6:2
E7:2
E8:2
E9:1
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,42
δ = 2,00 | w = 0,77
δ = 2,53 | w = 0,94
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,39
δ = 0,84 | w = 0,59
δ = 1,00 | w = 0,67
δ = 1,00 | w = 1,00


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:3
E2:5
E3:2
E4:2
E5:4
E6:2
E7:2
E8:2
E9:1
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,42
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,56
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,59
δ = 1,00 | w = 0,67
δ = 1,00 | w = 1,00


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:3
E2:5
E3:2
E4:2
E5:4
E6:2
E7:3
E8:2
E9:1
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1:3
E2:5
E3:2
E4:2
E5:4
E6:2
E7:3
E8:2
E9:1
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60
CONSTRUCTED ASSOCIATIVE NEURAL GRAPH

COMPUTING OF SYNAPTIC EFFICIENCIES AND WEIGHTS

Synaptic efficiencies and weights can be also computed off-line (batch) after presentation of all training sequences:

γ	4	$\Delta T - Ta$	δ
ω	100	0	1
Ts	2	17	0,534
TaMAX	15	34	0,310
		51	0,192
		68	0,126
		85	0,085
		102	0,060
		119	0,043
		136	0,032

			POSTSYNAPTIC AS-NEURON								
	η	$\Sigma\delta$	E1	E2	E3	E4	E5	E6	E7	E8	E9
PRESYNAPTIC AS-NEURON	3	E1	0,310	2,000	0,534						
	5	E2	0,534		2,000		0,534	1,000	0,310	1,000	
	2	E3	1,000				1,000		0,534		
	2	E4		1,534	0,534		1,310	0,310	0,192		
	4	E5	1,000	2,534				0,534	1,000	0,534	
	2	E6									
	3	E7		0,534			1,000	0,310		0,844	1,000
	2	E8						1,000			
	1	E9						0,534		1,000	

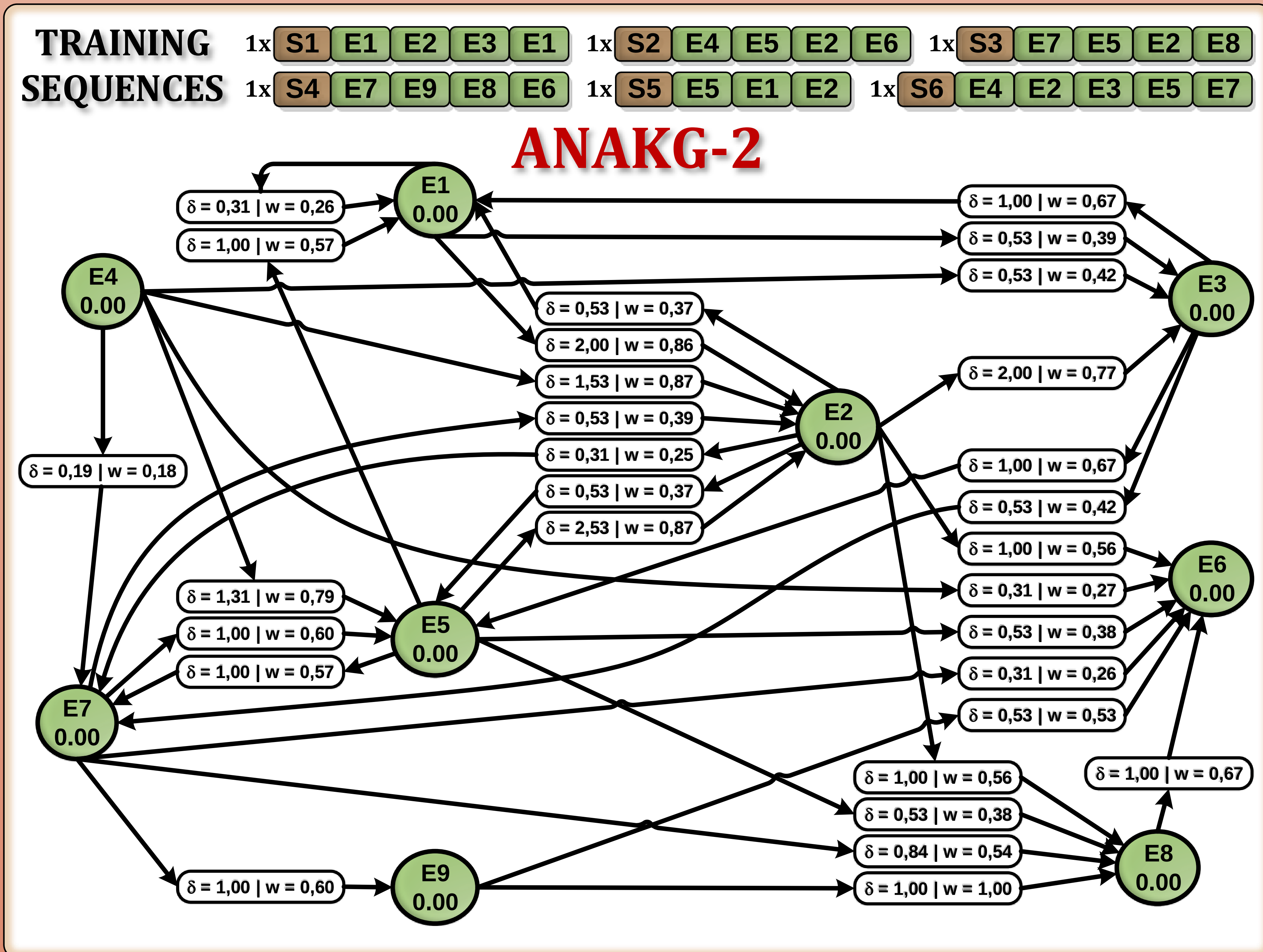
TRAINING SENTENCES	
1	E1-E2-E3-E1
2	E4-E5-E2-E6
3	E7-E5-E2-E8
4	E7-E9-E8-E6
5	E5-E1-E2
6	E4-E2-E3-E5-E7

			POSTSYNAPTIC AS-NEURON								
	θ	w	E1	E2	E3	E4	E5	E6	E7	E8	E9
PRESYNAPTIC AS-NEURON	1	E1	0,257	0,857	0,394						
	1	E2	0,374		0,769		0,374	0,556	0,248	0,556	
	1	E3	0,667				0,667		0,421		
	1	E4		0,868	0,421		0,792	0,269	0,175		
	1	E5	0,571	0,874				0,381	0,571	0,381	
	1	E6									
	1	E7		0,394			0,600	0,257		0,540	0,600
	1	E8						0,667			
	1	E9						0,534		1,000	

STIMULATION OF ASSOCIATIVE NEURAL GRAPHS

In order to use the construted associative neural graph:

1. Choose a combination or a sequence of the created as-neurons.
2. This combination/sequence forms a recalling context.
3. Activate this combination of neurons:
   - at the same time (for a simple combination)
   - or sequentially (for a sequence, sentence etc.).
4. Watch the associative reaction formed from activated as-neurons in various moments and sequences.
5. Your associative answer (recall) is given by the sequence(s) of values represented by the activated as-neurons and their order given by their activation moments.


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
ANAKG-2
E1 0.00
E2 0.00
E3 0.00
E4 0.00
E5 0.00
E6 0.00
E7 0.00
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

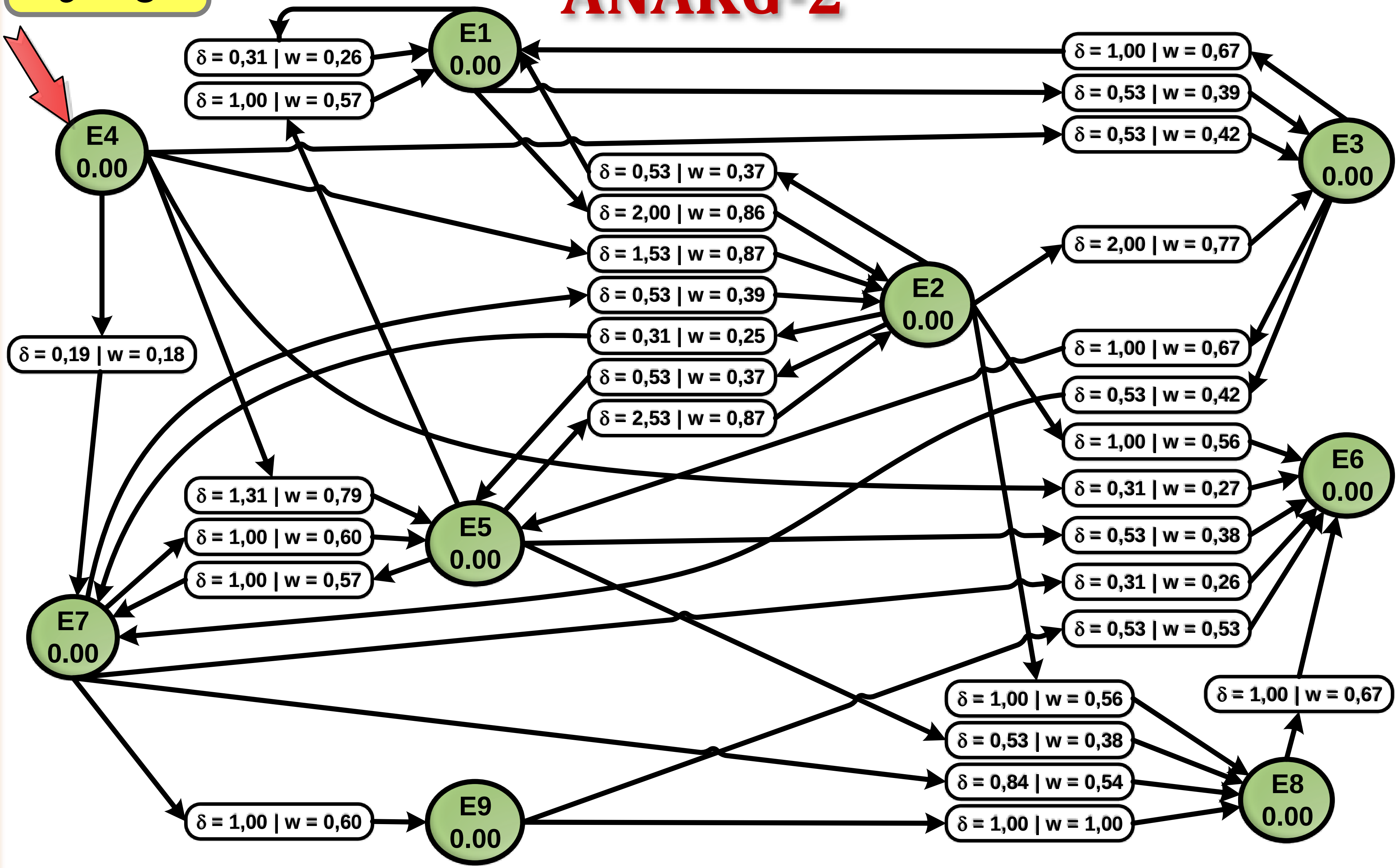
TRAINING SEQUENCES

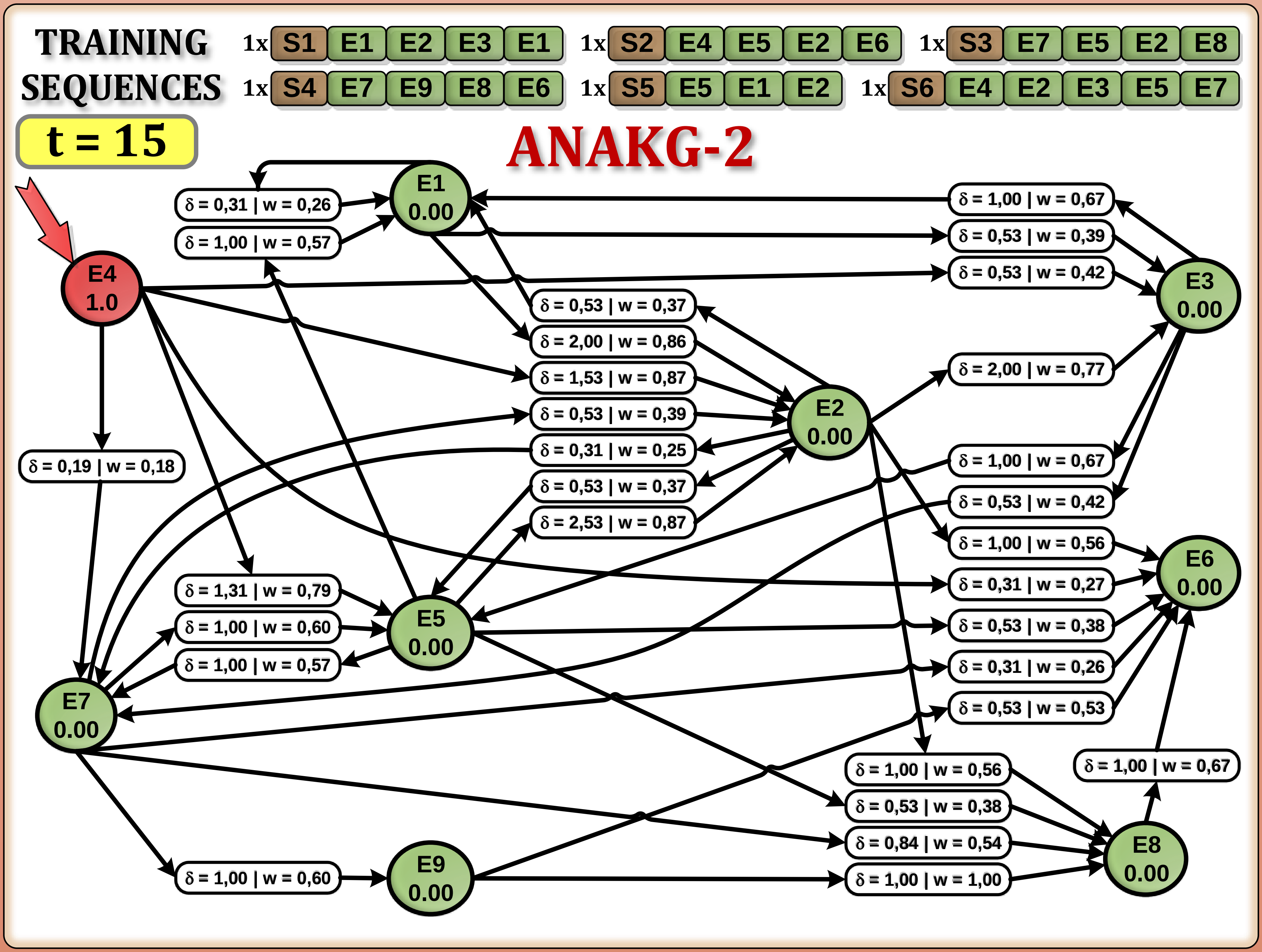
1x S1 E1 E2 E3 E1 — 1x S2 E4 E5 E2 E6 — 1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6 — 1x S5 E5 E1 E2 — 1x S6 E4 E2 E3 E5 E7

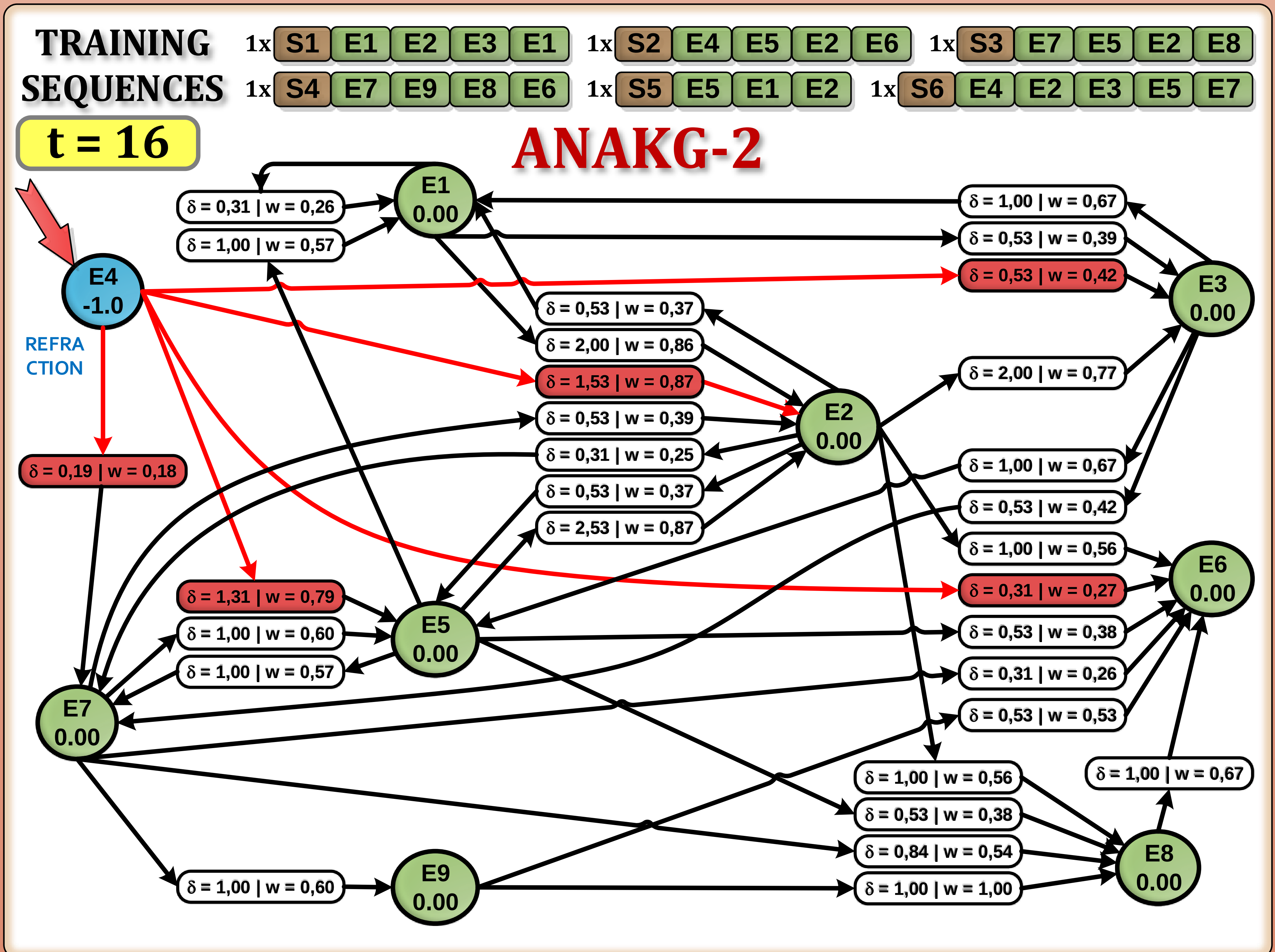
t = 0

ANAKG-2

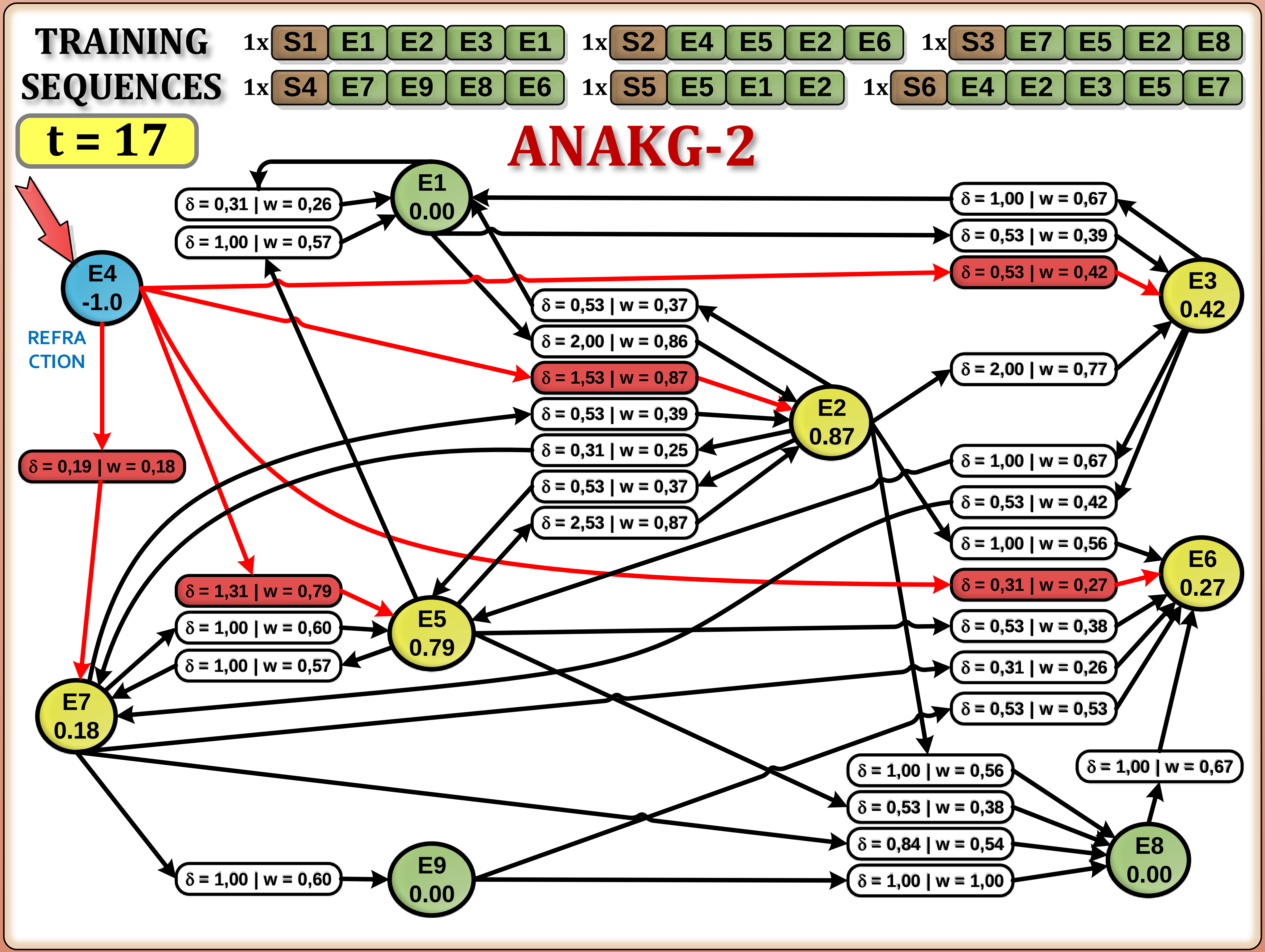


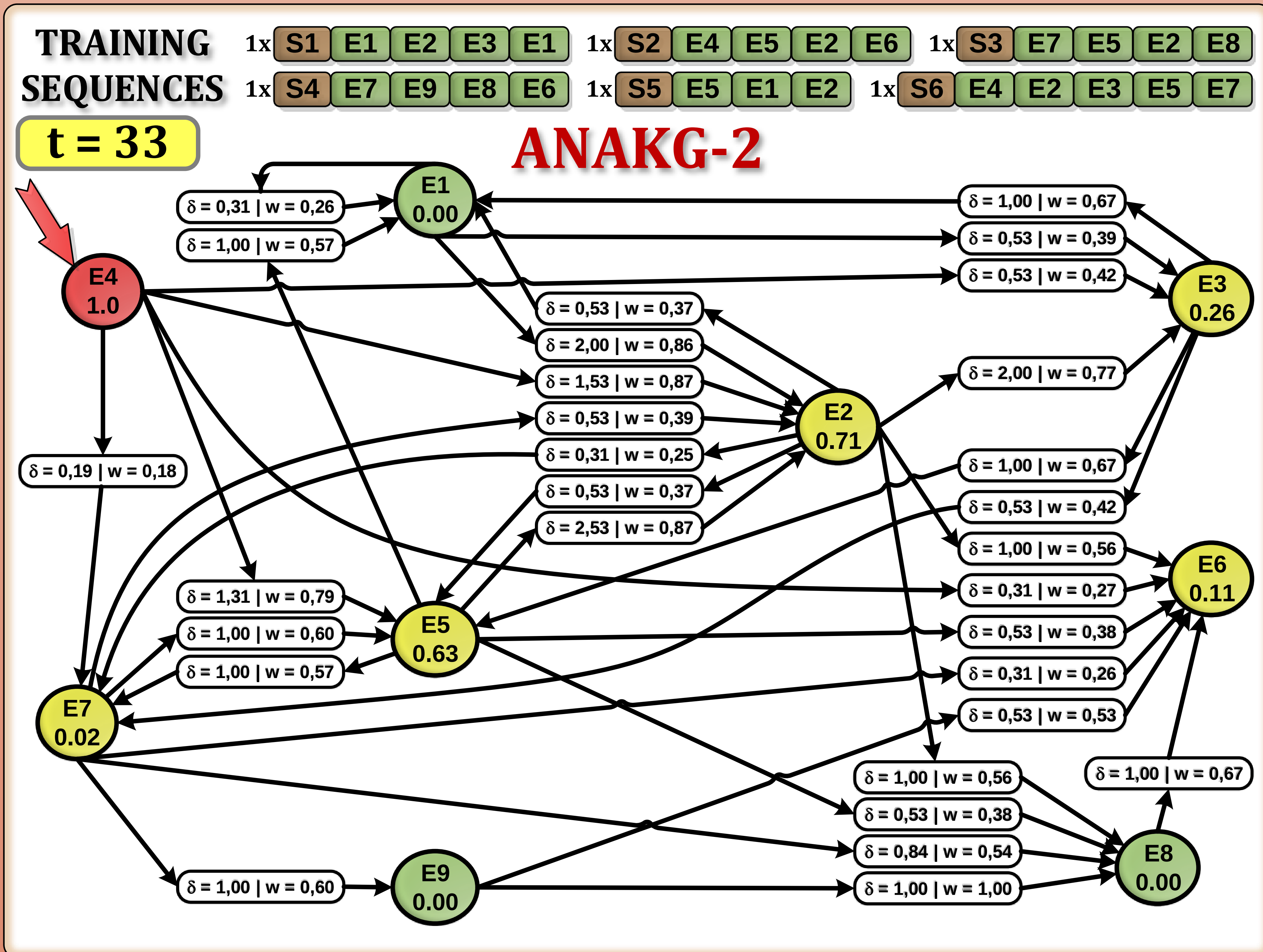


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 15
ANAKG-2
E1 0.00
E2 0.00
E3 0.00
E4 1.0
E5 0.00
E6 0.00
E7 0.00
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

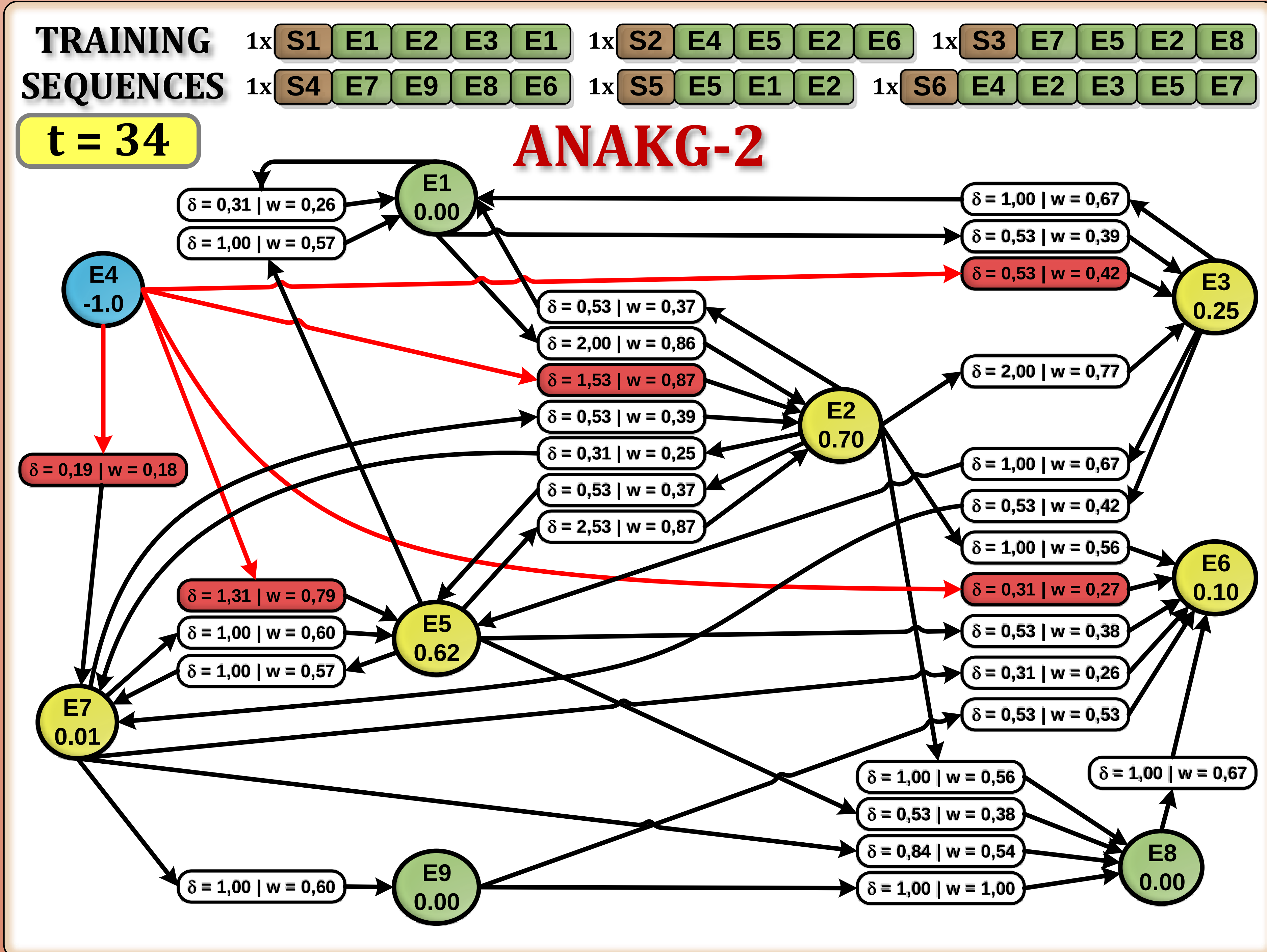


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 16
ANAKG-2
E1 0.00
E2 0.00
E3 0.00
E4 -1.0
E5 0.00
E6 0.00
E7 0.00
E8 0.00
E9 0.00
REFRACTION
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

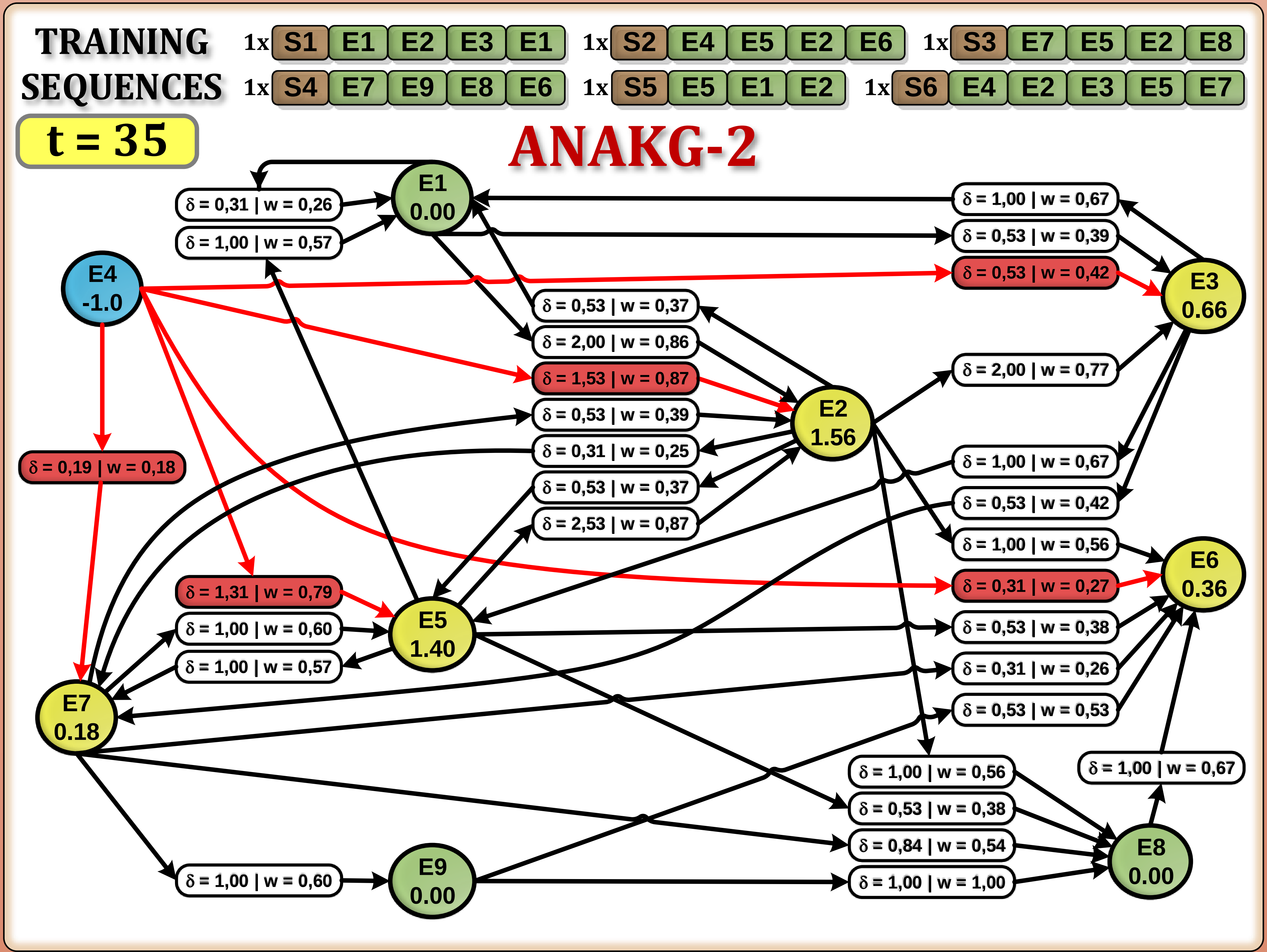

TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 17
ANAKG-2
E1 0.00
E2 0.87
E3 0.42
E4 -1.0
REFRA CTION
E5 0.79
E6 0.27
E7 0.18
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60



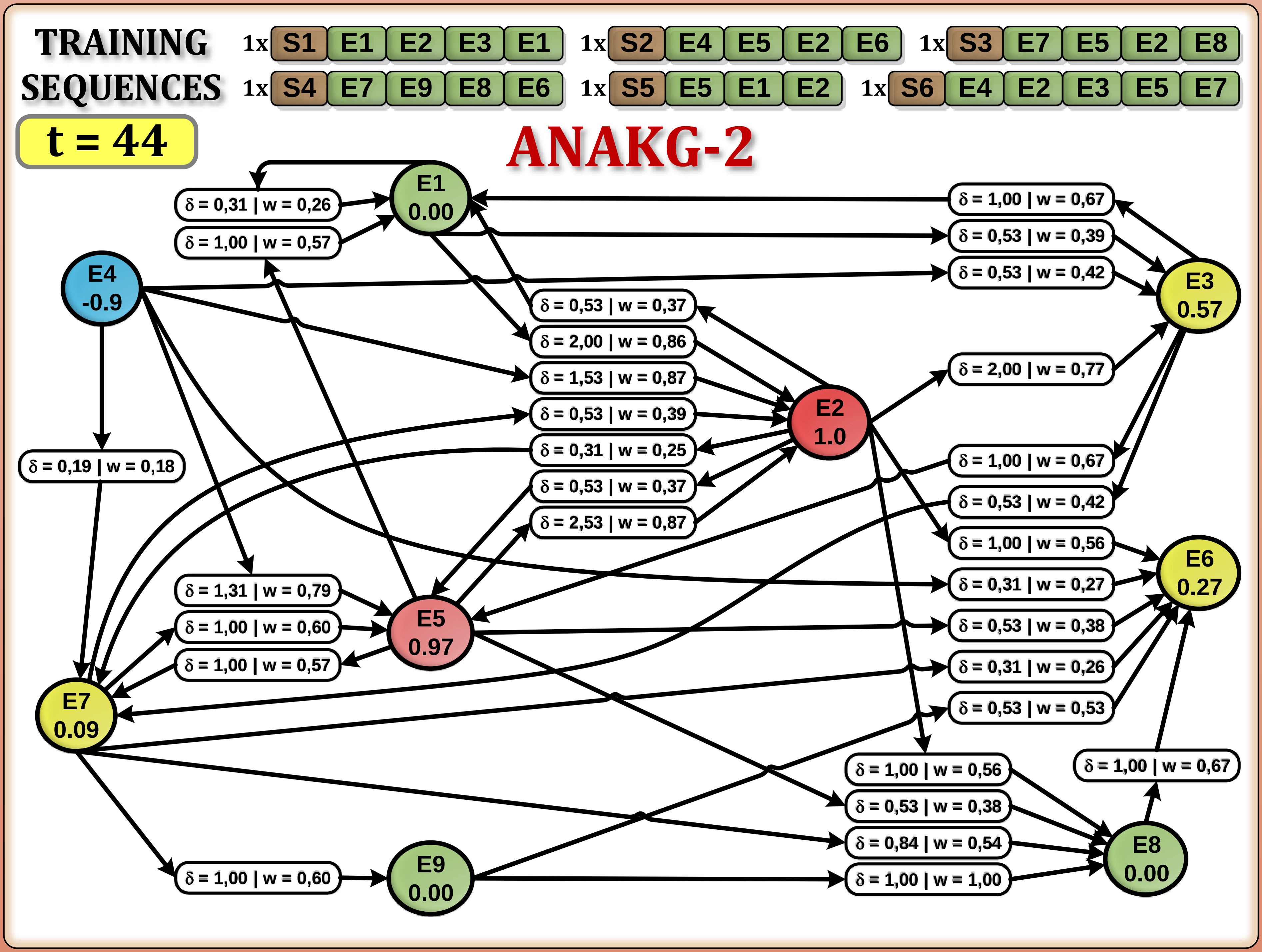
TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 33
ANAKG-2
E1 0.00
E2 0.71
E3 0.26
E4 1.0
E5 0.63
E6 0.11
E7 0.02
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

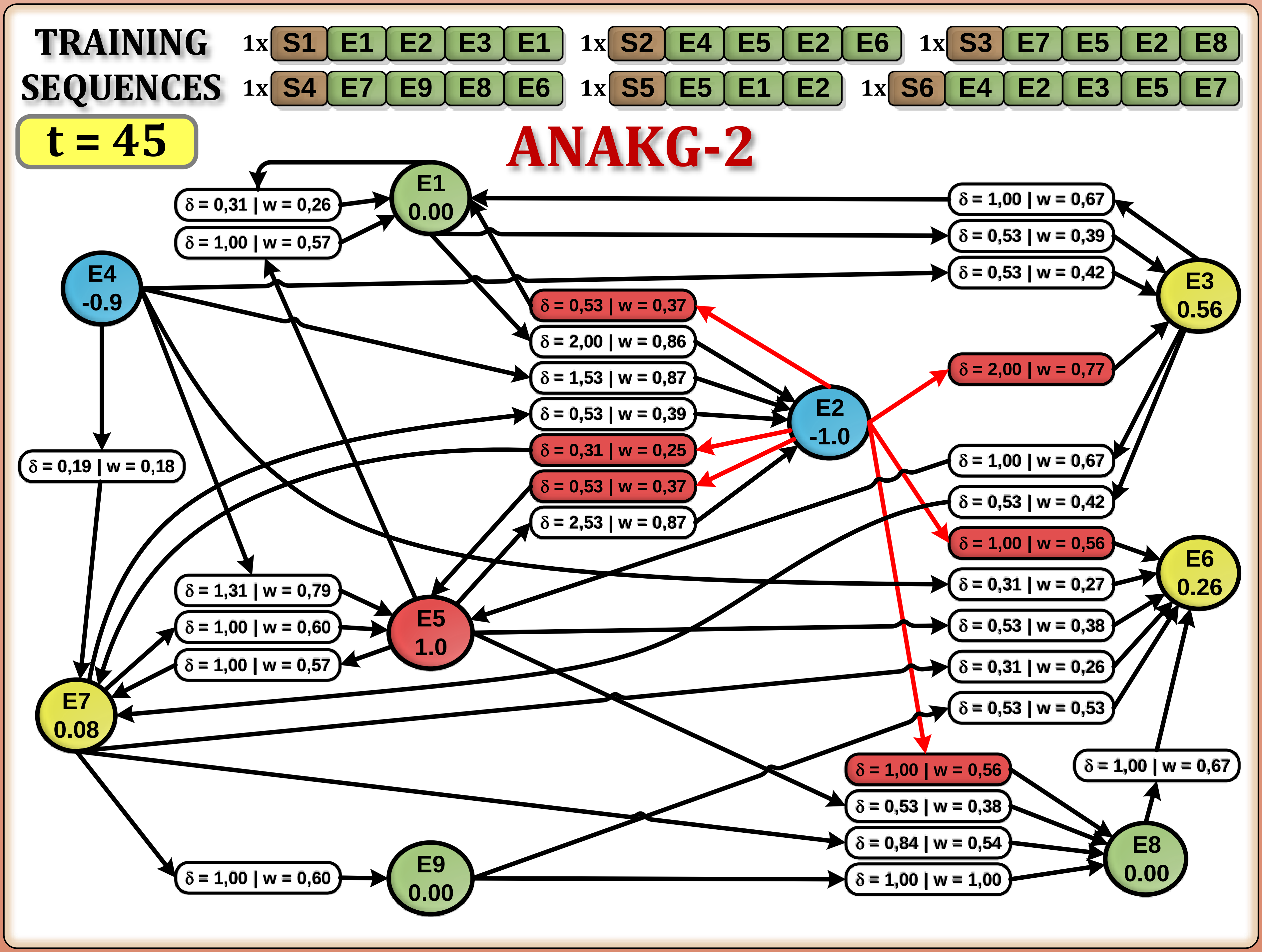


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 34
ANAKG-2
E1 0.00
E2 0.70
E3 0.25
E4 -1.0
E5 0.62
E6 0.10
E7 0.01
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

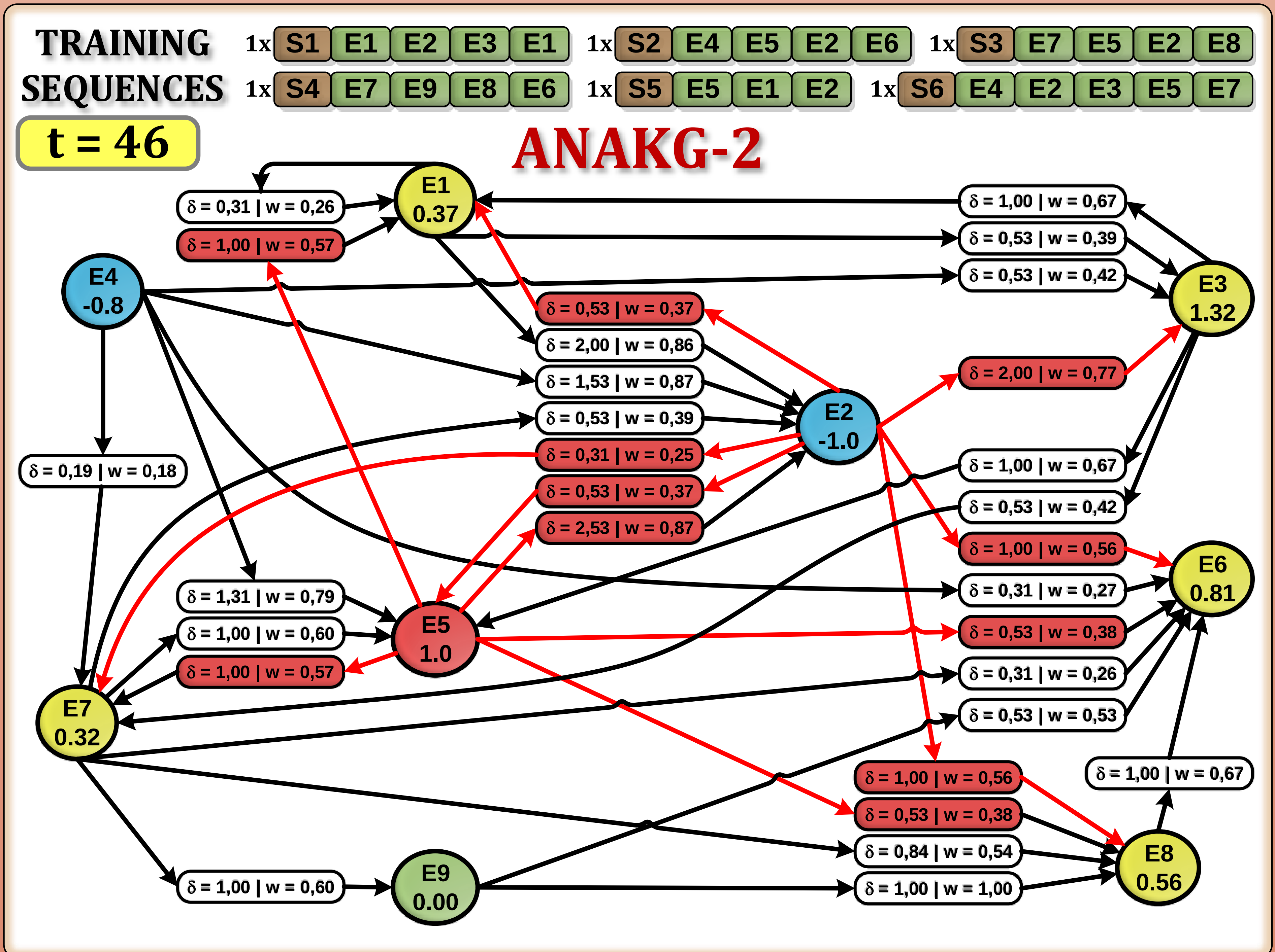


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 35
ANAKG-2
E1 0.00
E2 1.56
E3 0.66
E4 -1.0
E5 1.40
E6 0.36
E7 0.18
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60


TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 44
ANAKG-2
E1 0.00
E2 1.0
E3 0.57
E4 -0.9
E5 0.97
E6 0.27
E7 0.09
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60



TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 45
ANAKG-2
E1 0.00
E2 -1.0
E3 0.56
E4 -0.9
E5 1.0
E6 0.26
E7 0.08
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 0,19 | w = 0,18
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00



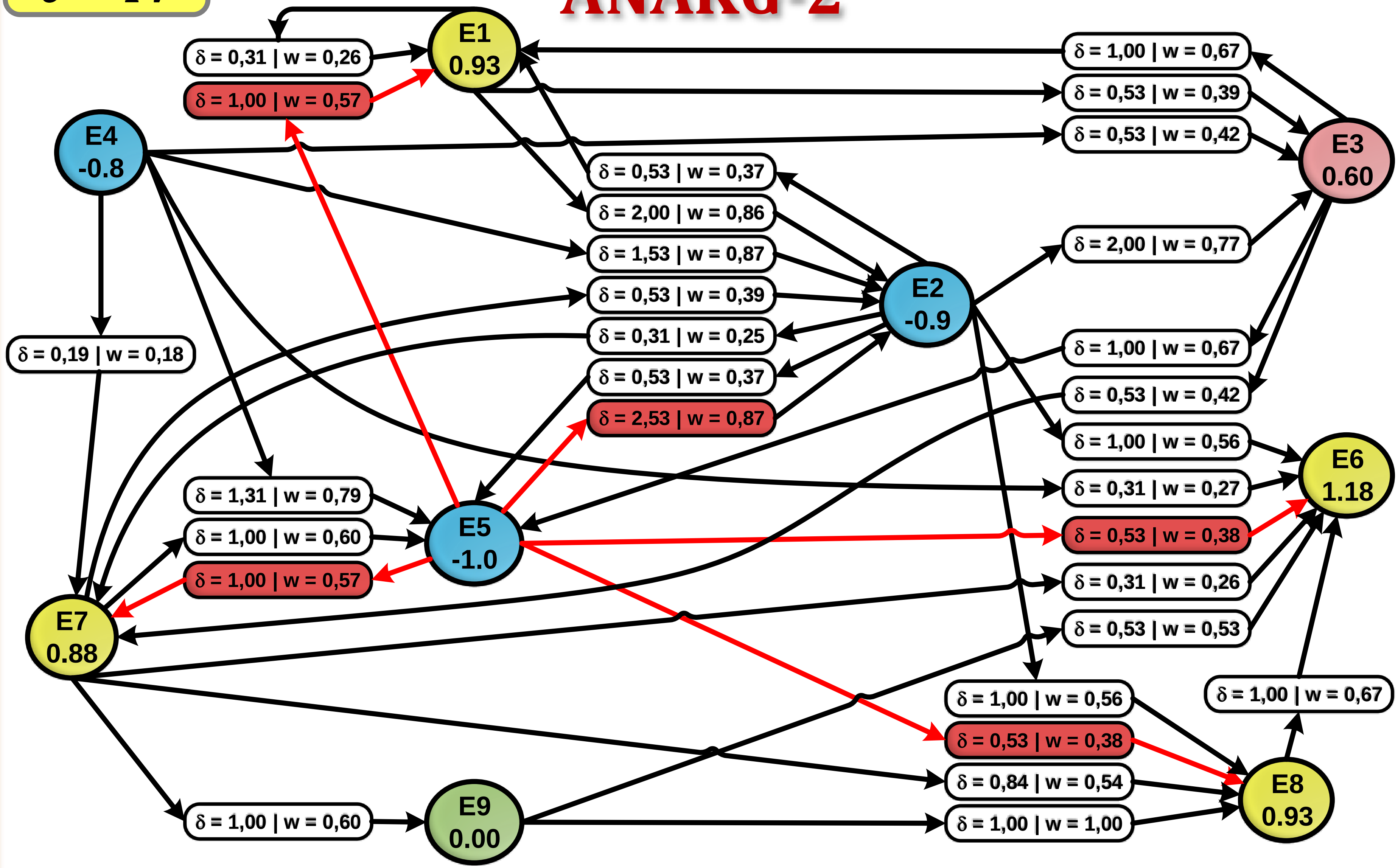
TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 46
ANAKG-2
E1 0.37
E2 -1.0
E3 1.32
E4 -0.8
E5 1.0
E6 0.81
E7 0.32
E8 0.56
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 0,19 | w = 0,18
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

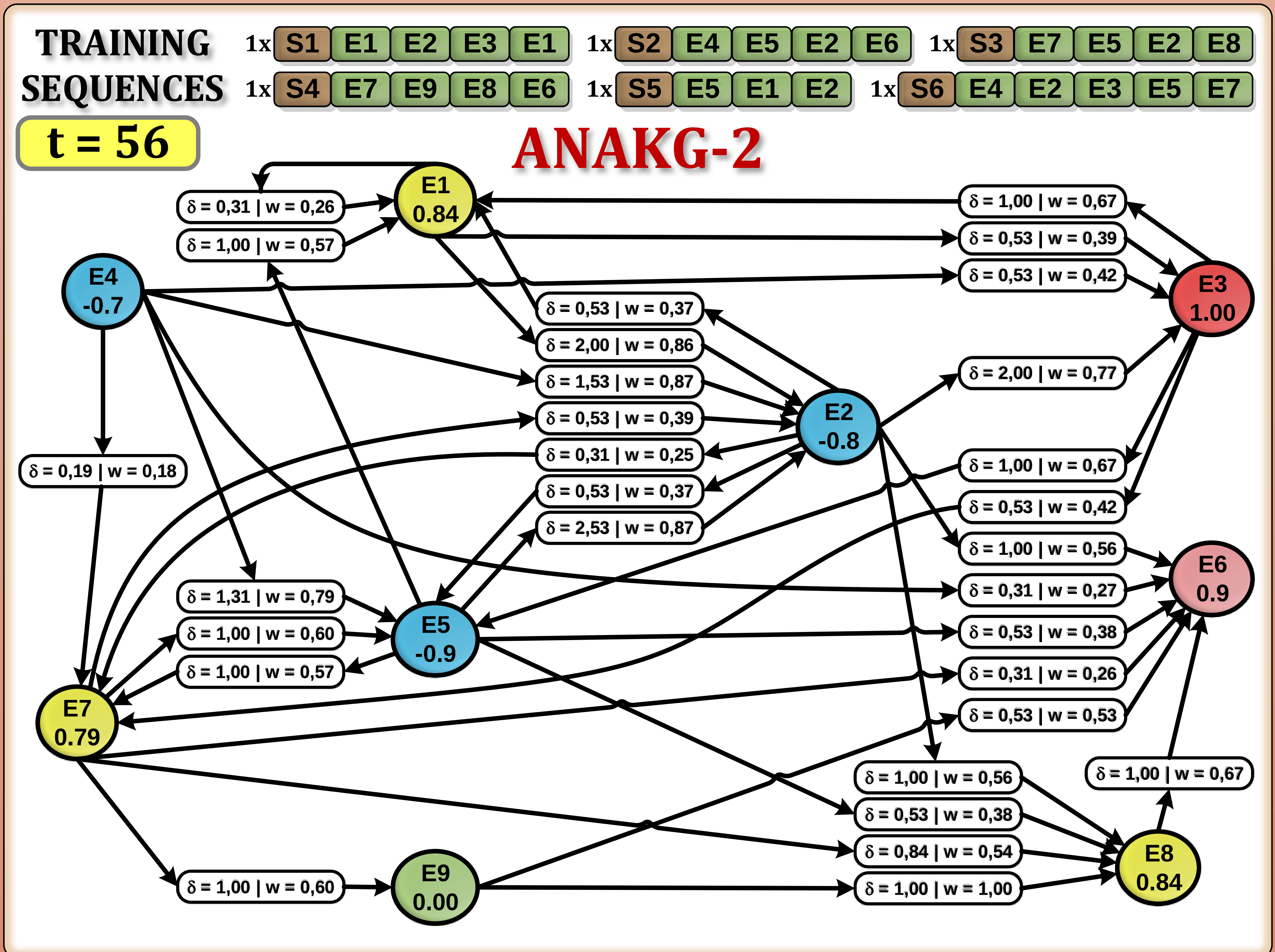
TRAINING SEQUENCES

1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7

t = 47

ANAKG-2





TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 56
ANAKG-2
E1 0.84
E2 -0.8
E3 1.00
E4 -0.7
E5 -0.9
E6 0.9
E7 0.79
E8 0.84
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,60

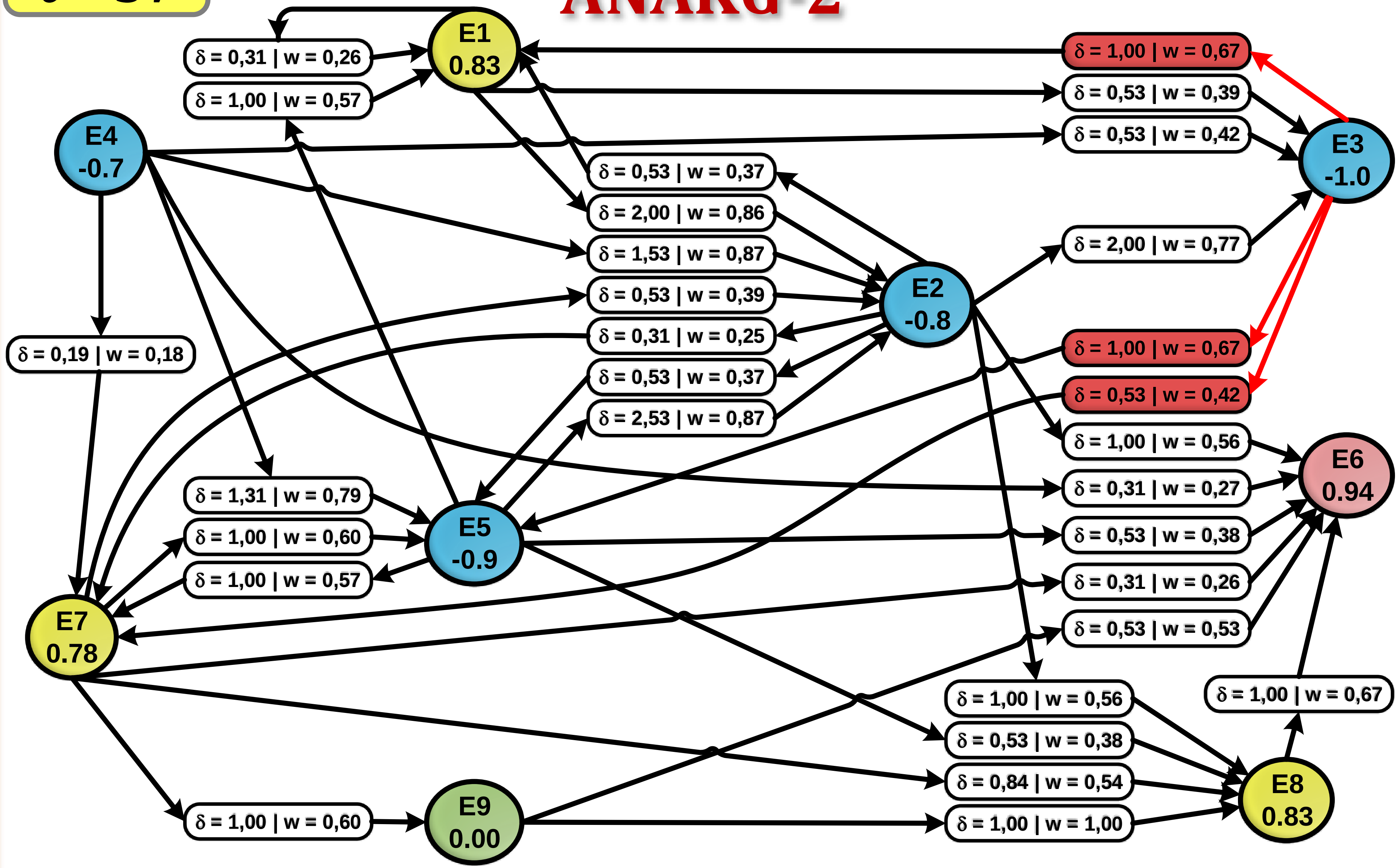
TRAINING SEQUENCES

1x S1 E1 E2 E3 E1   1x S2 E4 E5 E2 E6   1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6   1x S5 E5 E1 E2   1x S6 E4 E2 E3 E5 E7

t = 57

ANAKG-2



TRAINING SEQUENCES

1x S1 E1 E2 E3 E1

1x S2 E4 E5 E2 E6

1x S3 E7 E5 E2 E8

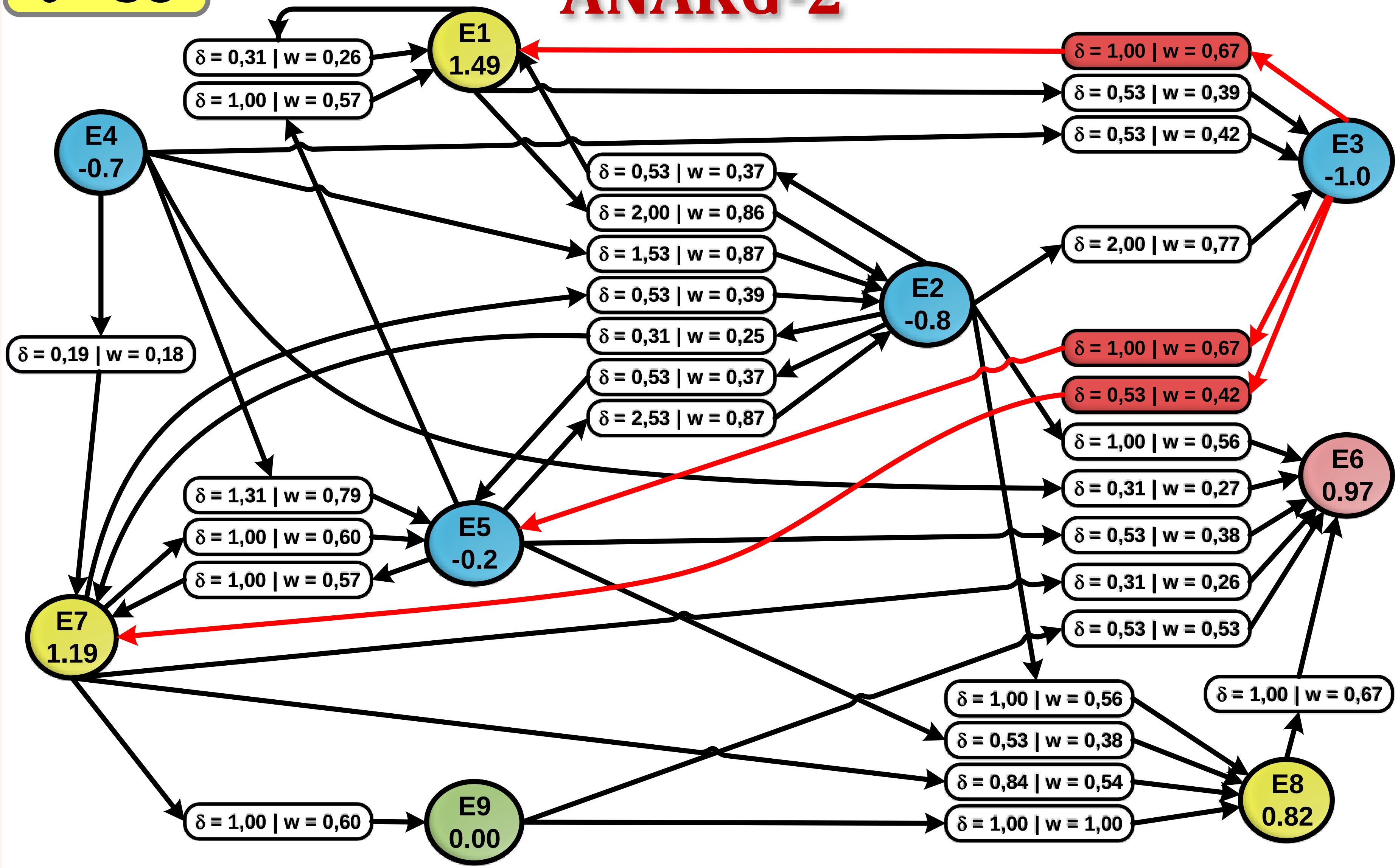
1x S4 E7 E9 E8 E6

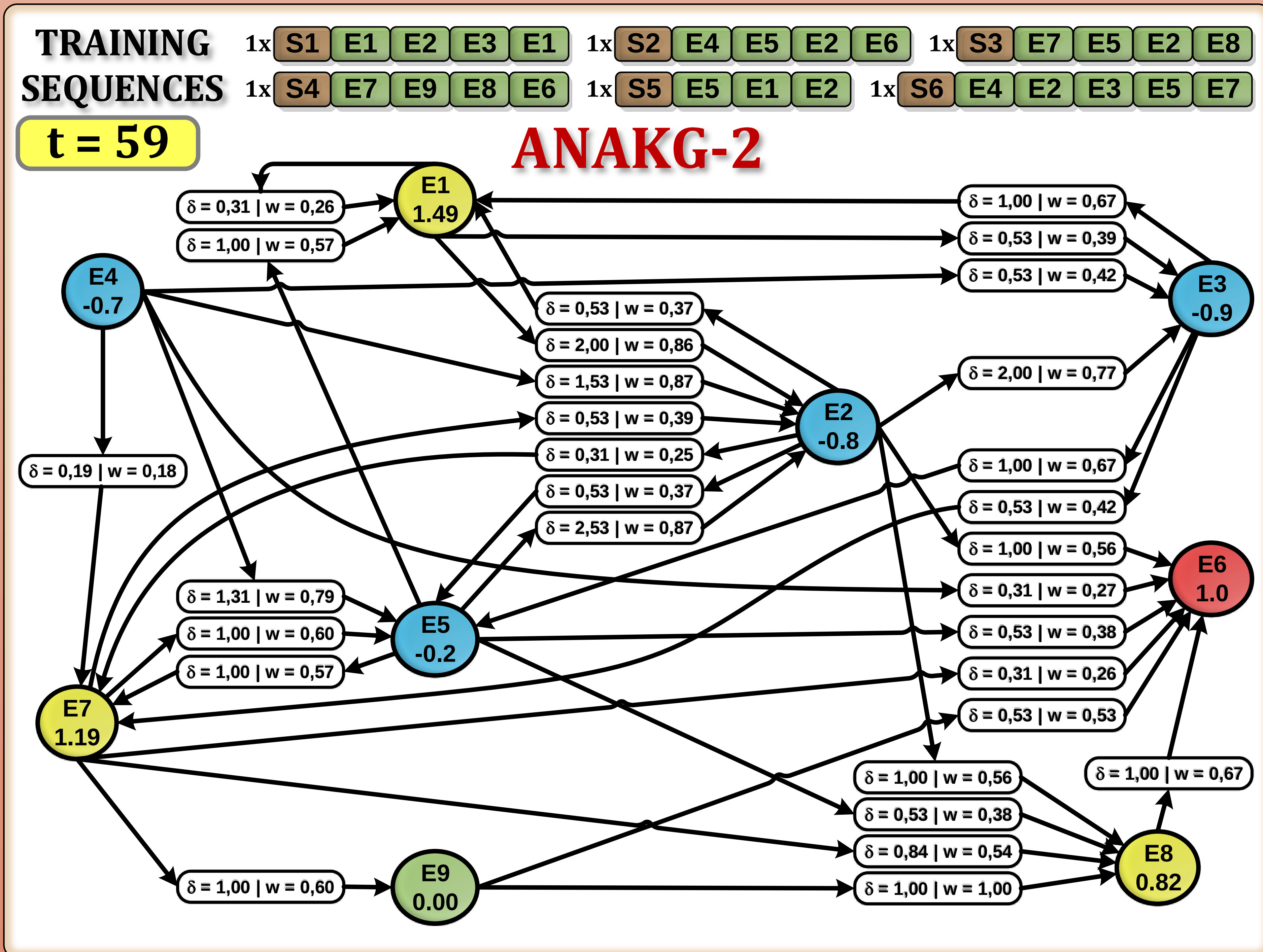
1x S5 E5 E1 E2

1x S6 E4 E2 E3 E5 E7

t = 58

ANAKG-2




TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 59
ANAKG-2
E1 1.49
E2 -0.8
E3 -0.9
E4 -0.7
E5 -0.2
E6 1.0
E7 1.19
E8 0.82
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 0,60
δ = 1,00 | w = 1,00

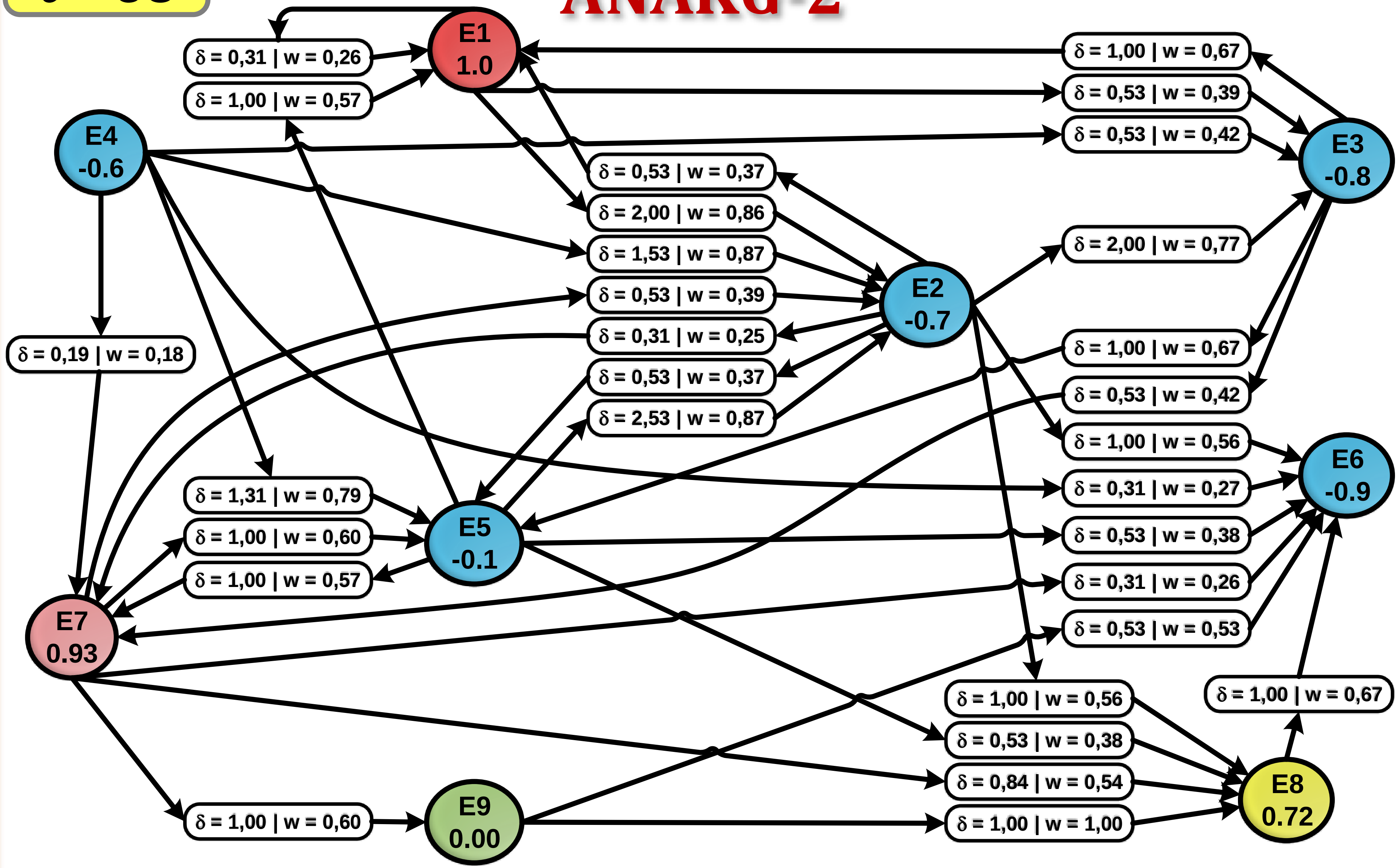
TRAINING SEQUENCES

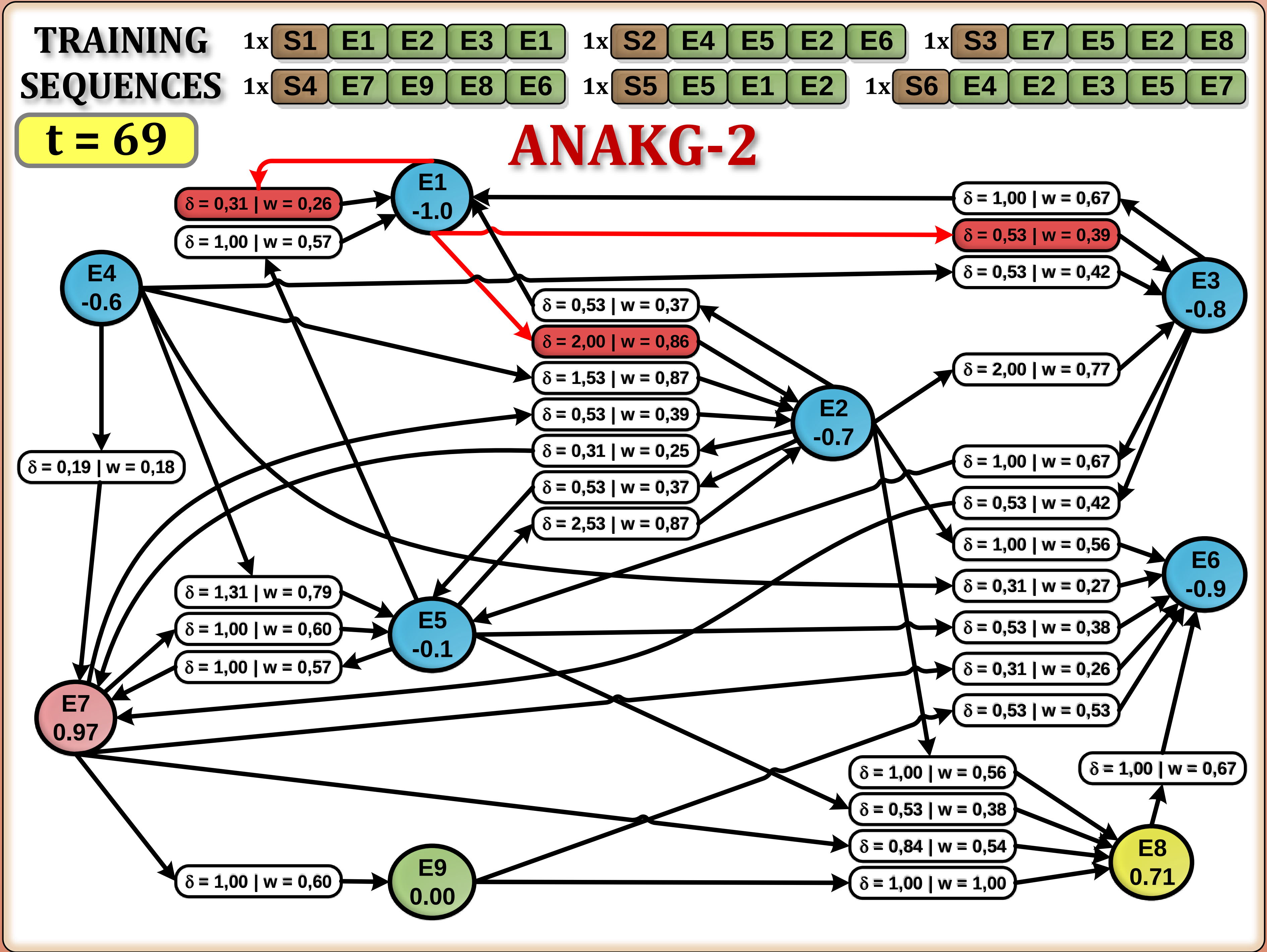
1x S1 E1 E2 E3 E1 1x S2 E4 E5 E2 E6 1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6 1x S5 E5 E1 E2 1x S6 E4 E2 E3 E5 E7

t = 68

ANAKG-2



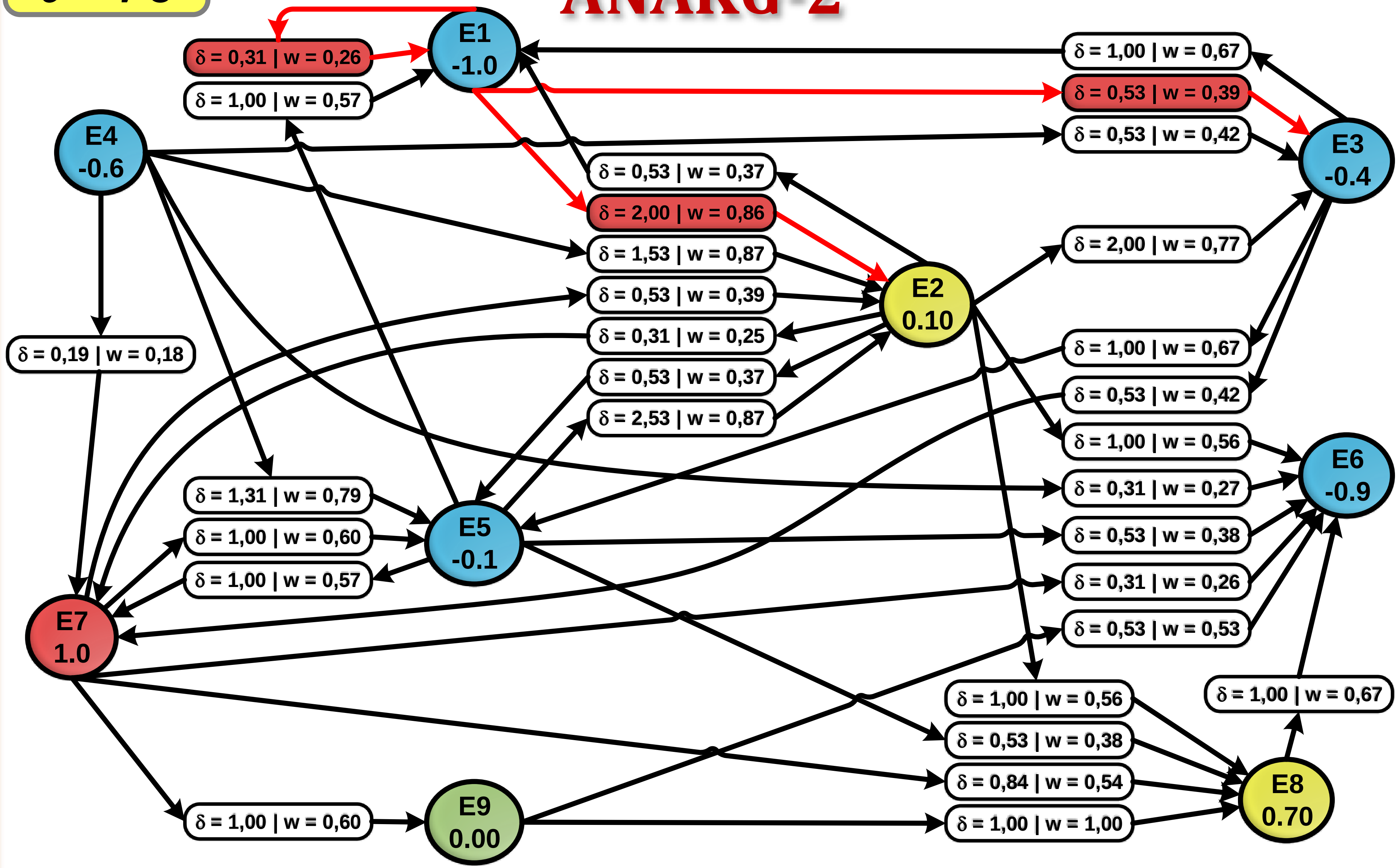

TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 69
ANAKG-2
E1 -1.0
E2 -0.7
E3 -0.8
E4 -0.6
E5 -0.1
E6 -0.9
E7 0.97
E8 0.71
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7

t = 70

ANAKG-2



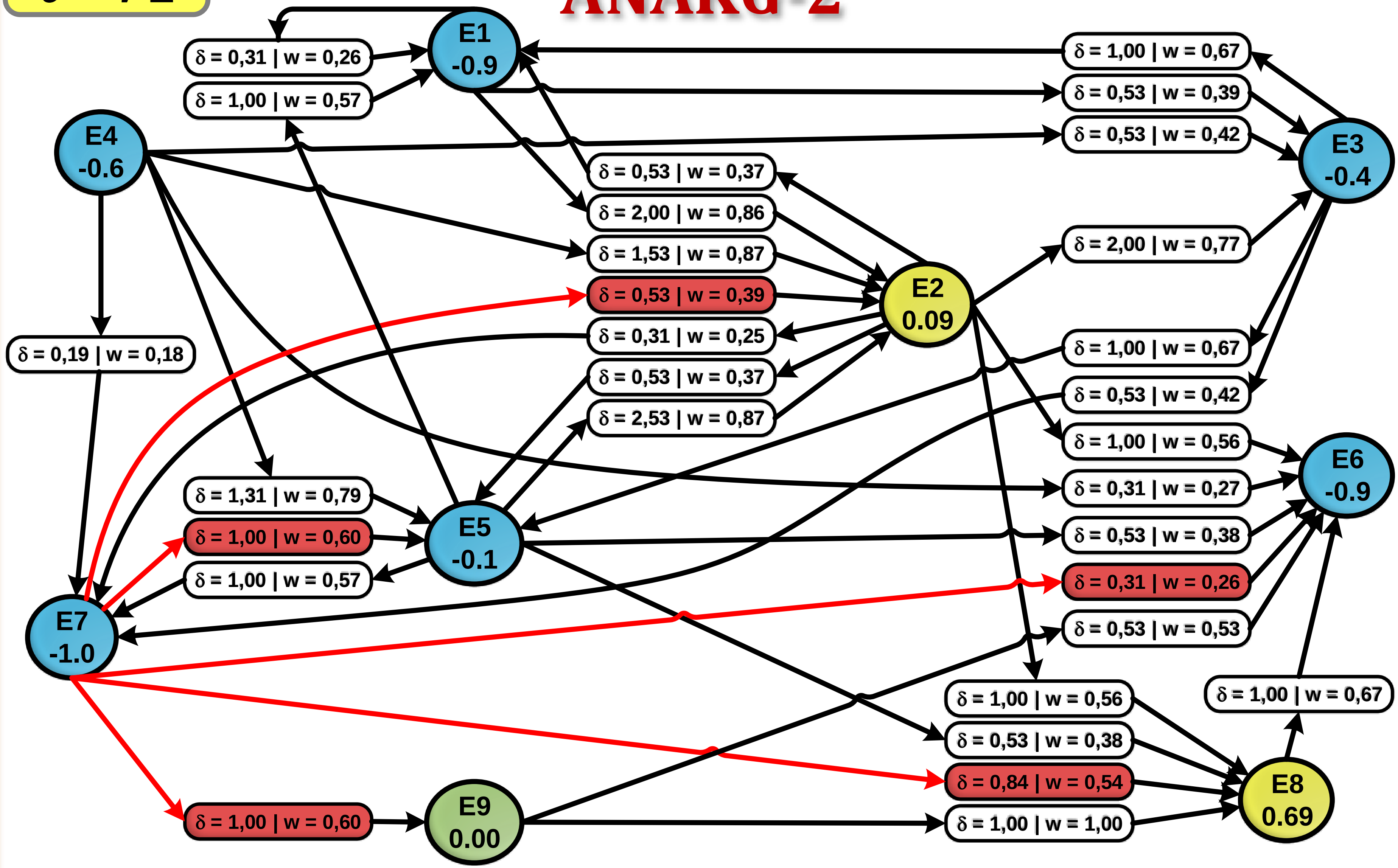
TRAINING SEQUENCES

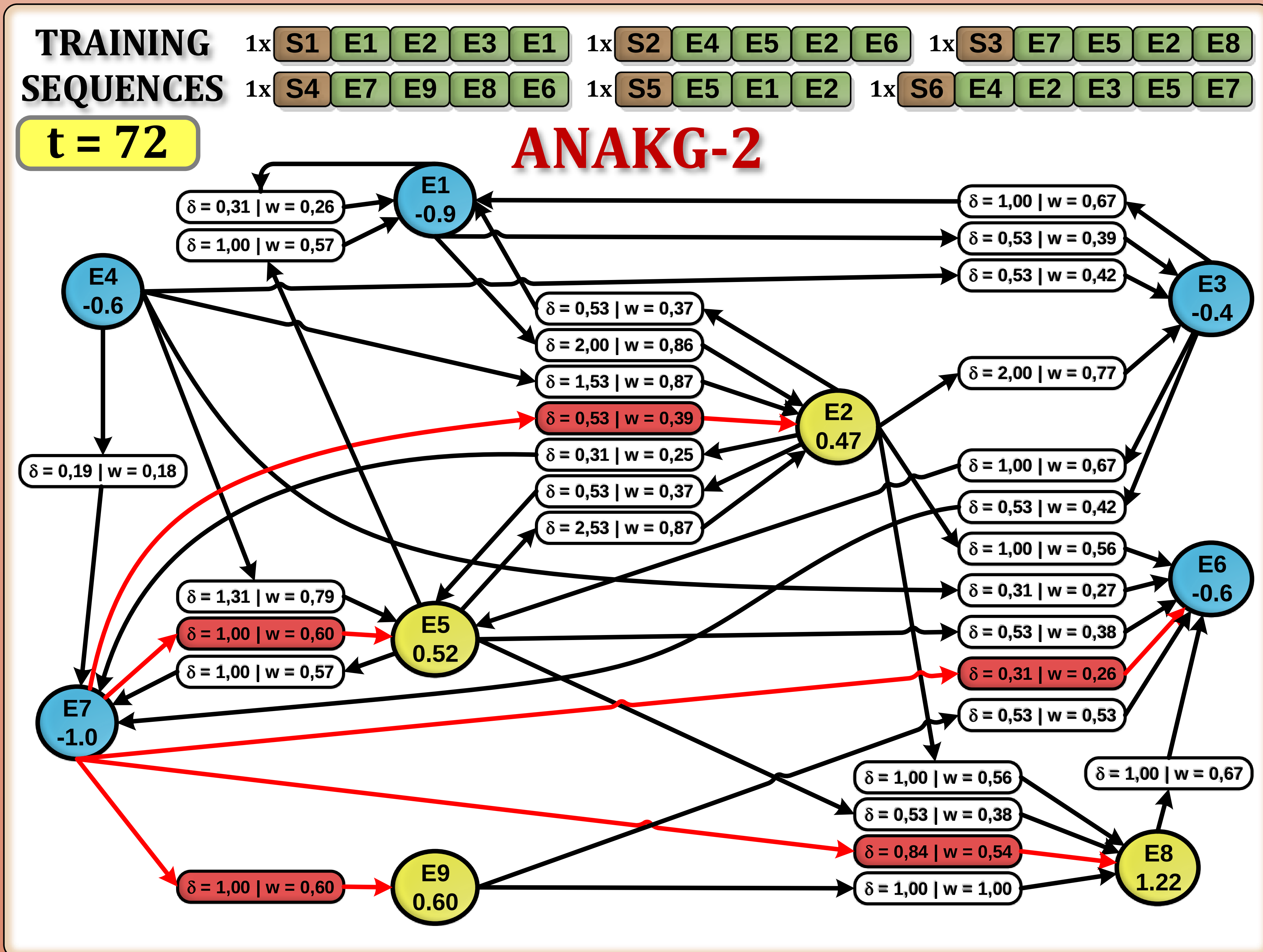
1x S1 E1 E2 E3 E1 | 1x S2 E4 E5 E2 E6 | 1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6 | 1x S5 E5 E1 E2 | 1x S6 E4 E2 E3 E5 E7

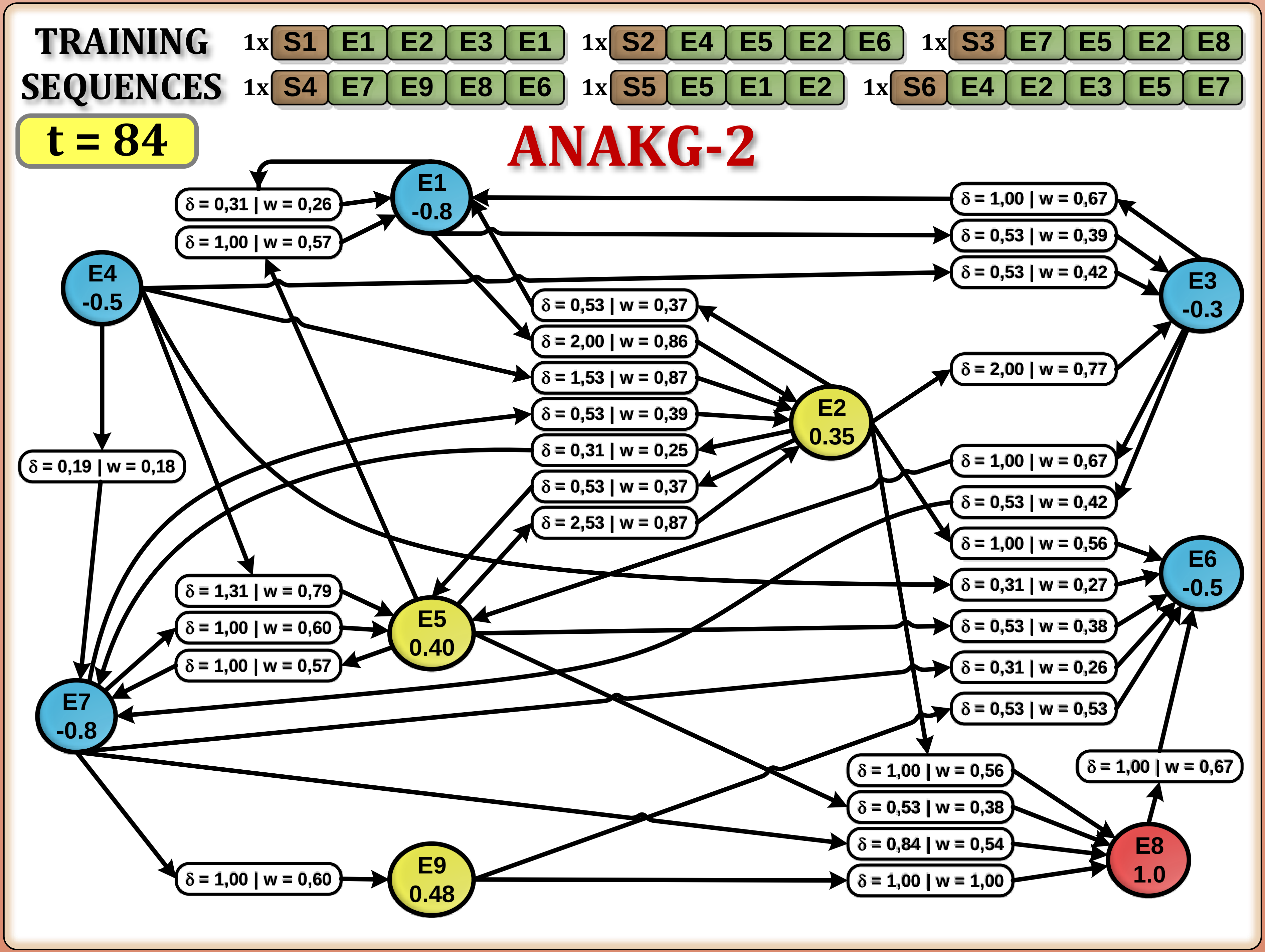
t = 71

ANAKG-2

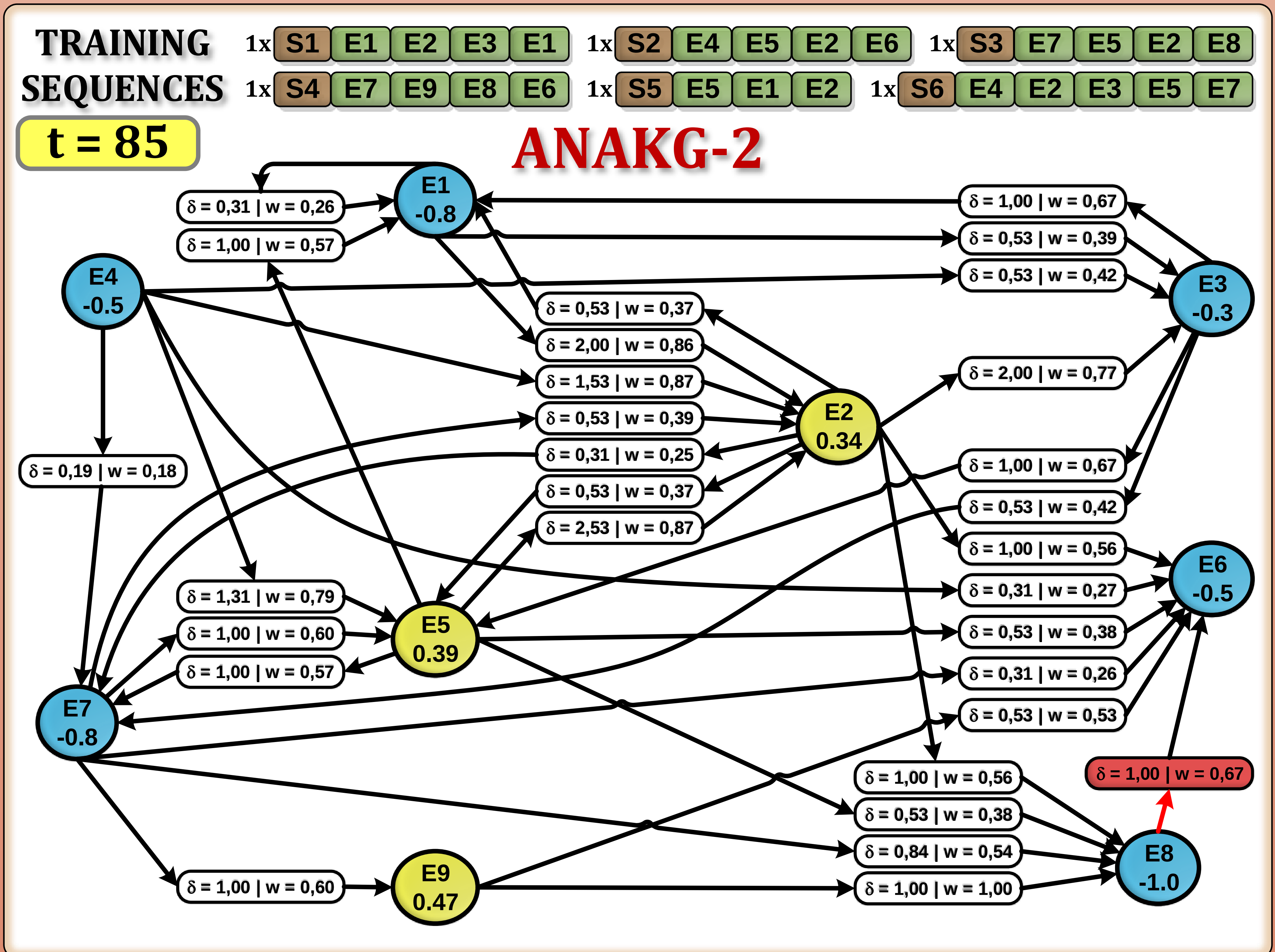




TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 72
ANAKG-2
E1 -0.9
E2 0.47
E3 -0.4
E4 -0.6
E5 0.52
E6 -0.6
E7 -1.0
E8 1.22
E9 0.60
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60



TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 84
ANAKG-2
E1 -0.8
E2 0.35
E3 -0.3
E4 -0.5
E5 0.40
E6 -0.5
E7 -0.8
E8 1.0
E9 0.48
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60



TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 85
ANAKG-2
E1 -0.8
E2 0.34
E3 -0.3
E4 -0.5
E5 0.39
E6 -0.5
E7 -0.8
E8 -1.0
E9 0.47
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,60

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1

1x S2 E4 E5 E2 E6

1x S3 E7 E5 E2 E8

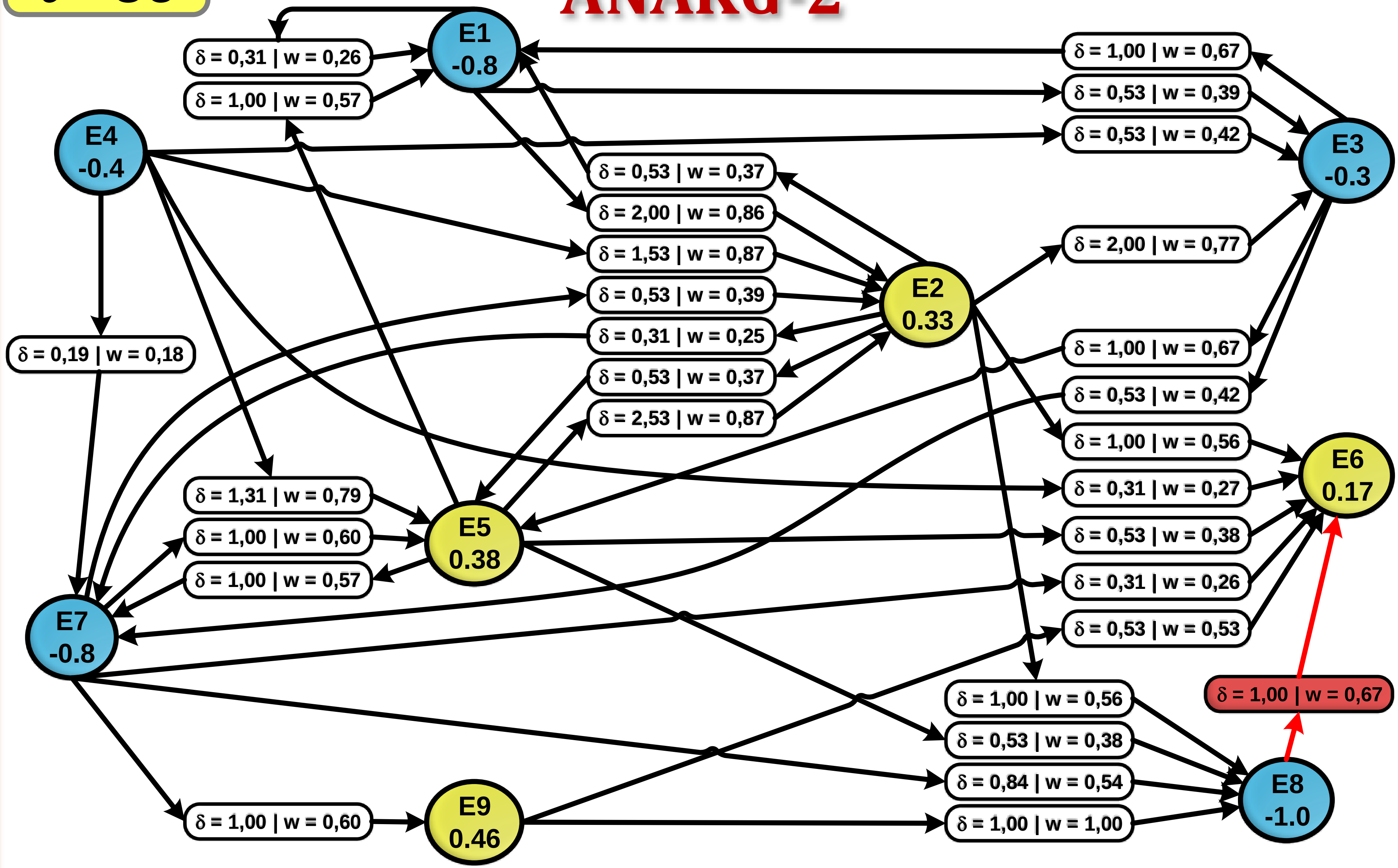
1x S4 E7 E9 E8 E6

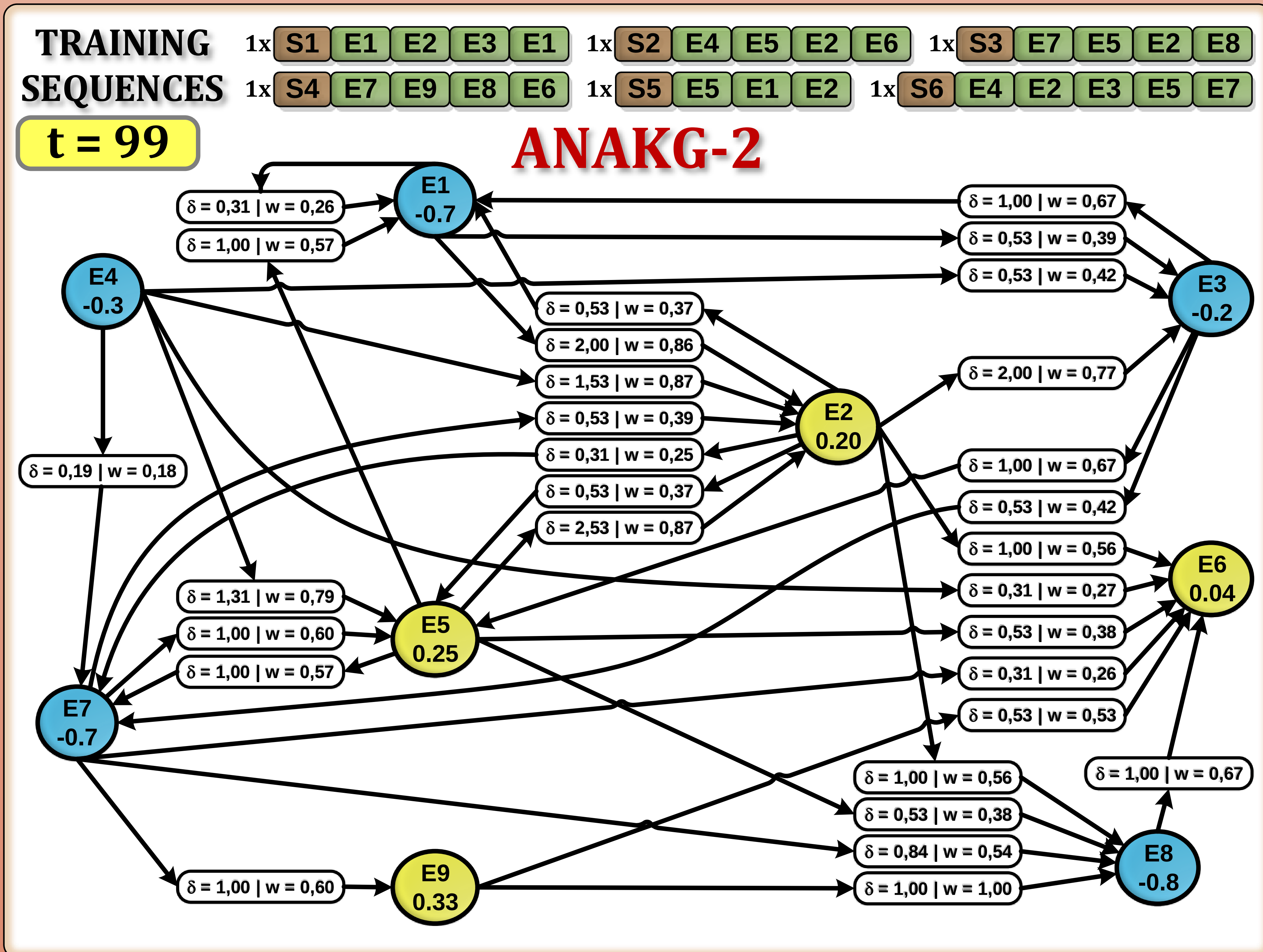
1x S5 E5 E1 E2

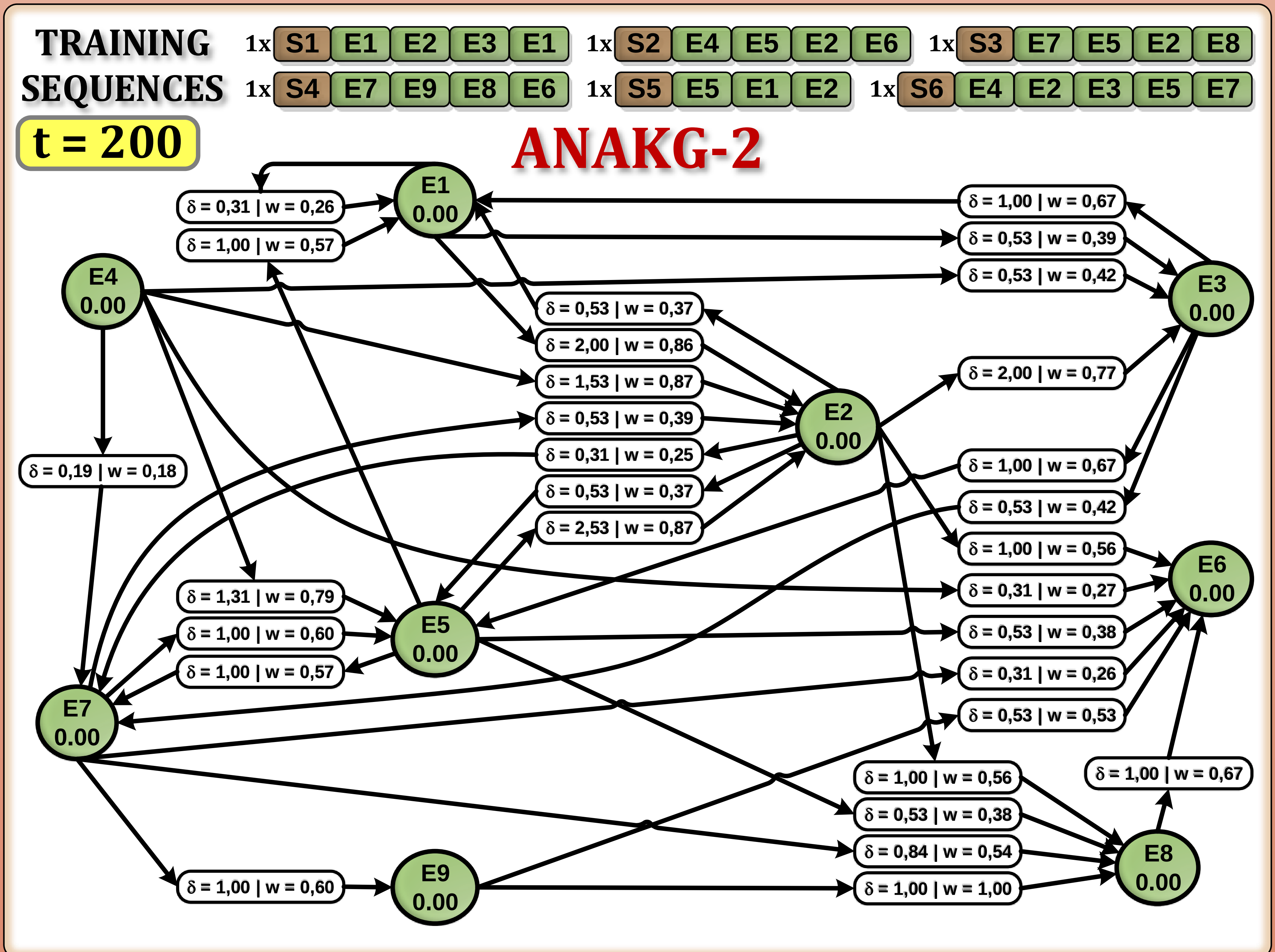
1x S6 E4 E2 E3 E5 E7

t = 86

ANAKG-2




TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 99
ANAKG-2
E1 -0.7
E2 0.20
E3 -0.2
E4 -0.3
E5 0.25
E6 0.04
E7 -0.7
E8 -0.8
E9 0.33
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60



TRAINING SEQUENCES
1x S1 E1 E2 E3 E1
1x S2 E4 E5 E2 E6
1x S3 E7 E5 E2 E8
1x S4 E7 E9 E8 E6
1x S5 E5 E1 E2
1x S6 E4 E2 E3 E5 E7
t = 200
ANAKG-2
E1 0.00
E2 0.00
E3 0.00
E4 0.00
E5 0.00
E6 0.00
E7 0.00
E8 0.00
E9 0.00
δ = 0,31 | w = 0,26
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,39
δ = 0,53 | w = 0,42
δ = 0,53 | w = 0,37
δ = 2,00 | w = 0,86
δ = 1,53 | w = 0,87
δ = 0,53 | w = 0,39
δ = 0,31 | w = 0,25
δ = 0,53 | w = 0,37
δ = 2,53 | w = 0,87
δ = 2,00 | w = 0,77
δ = 0,19 | w = 0,18
δ = 1,00 | w = 0,67
δ = 0,53 | w = 0,42
δ = 1,00 | w = 0,56
δ = 0,31 | w = 0,27
δ = 0,53 | w = 0,38
δ = 0,31 | w = 0,26
δ = 0,53 | w = 0,53
δ = 1,31 | w = 0,79
δ = 1,00 | w = 0,60
δ = 1,00 | w = 0,57
δ = 1,00 | w = 0,56
δ = 0,53 | w = 0,38
δ = 0,84 | w = 0,54
δ = 1,00 | w = 1,00
δ = 1,00 | w = 0,67
δ = 1,00 | w = 0,60

What is the interpretation of these activations?

TRAINING SEQUENCES

1x S1 E1 E2 E3 E1 1x S2 E4 E5 E2 E6 1x S3 E7 E5 E2 E8

1x S4 E7 E9 E8 E6 1x S5 E5 E1 E2 1x S6 E4 E2 E3 E5 E7

We got a new sequence:

S E4 E4 E2 E5 E3 E6 E1 E7 E8

Training sequences have no meaning.

There is no interpretation of this result sequence.

We have to take real training sequences to be able to interpret results of activations.

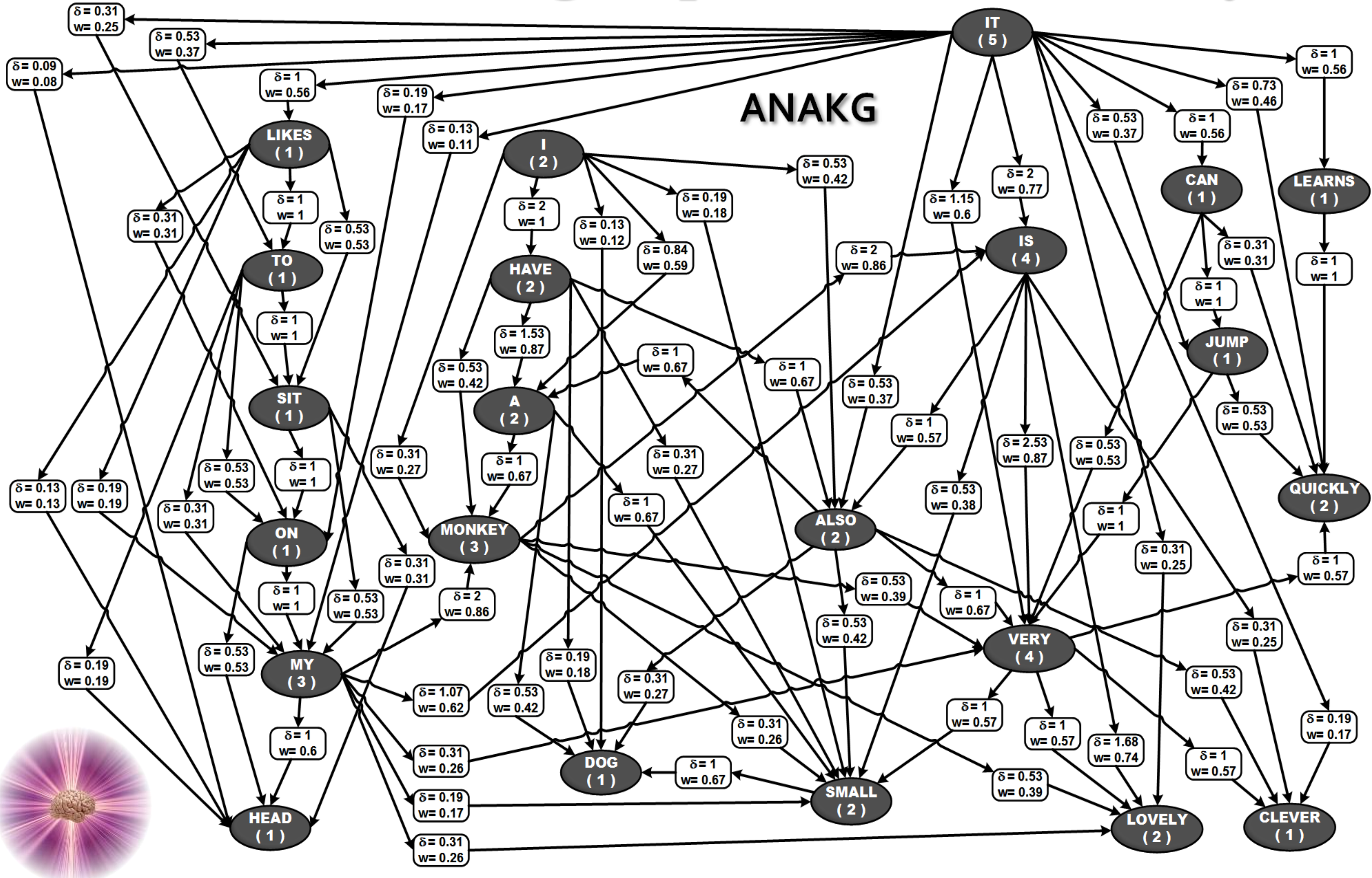
MONKEY

TRAINING SEQUENCE SET:

"I have a monkey. My monkey is very small. It is very lovely. It likes to sit on my head. It can jump very quickly. It is also very clever. It learns quickly. My monkey is lovely. I have also a small dog."

QUESTION: What is this monkey like?

Associative Neural Graph ANAKG-2 for training sequence set „Monkey”



COMPUTATION OF SYNAPTIC EFFICIENCES AND NUMBERS OF ACTIVATIONS OF ALL NEURONS

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S} \;:\; (\dots \rightsquigarrow S \rightsquigarrow \dots \rightsquigarrow \widehat{S} \rightsquigarrow \dots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t - t_a^{\widehat{S}}}{\omega}} \right)^{\gamma} \qquad (1)$$

$\omega = 100$
$t_a^{MAX} = 15$
$t_s = 5$
$t_r = 3$
$\theta = 1$
$\gamma = 4$

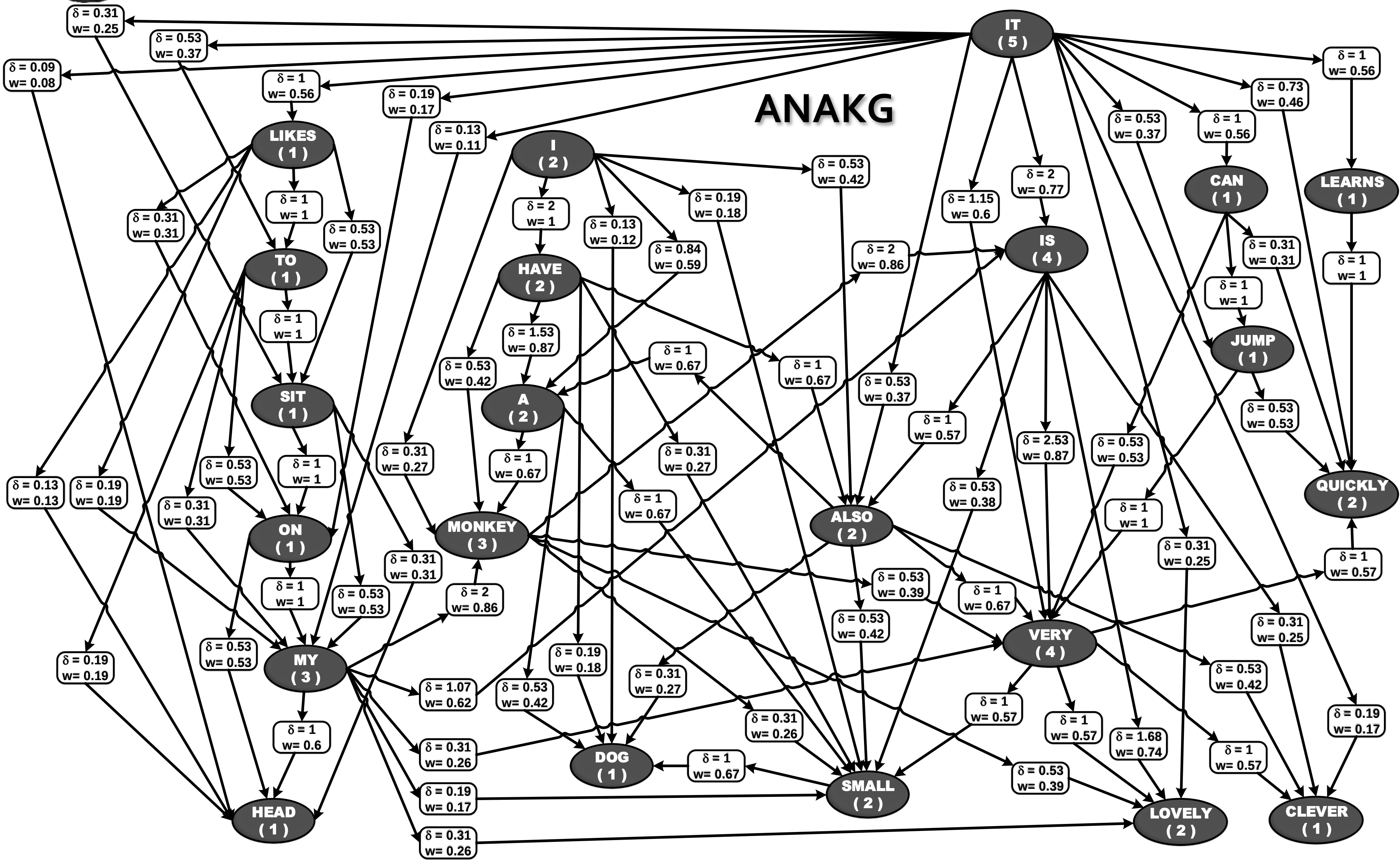
			POSTSYNAPTIC AS-NEURON																					
	η	Σδ	A	ALSO	CAN	CLEVER	DOG	HAVE	HEAD	I	IS	IT	JUMP	LEARNS	LIKES	LOVELY	MONKEY	MY	ON	QUICKLY	SIT	SMALL	TO	VERY
PRESYNAPTIC AS-NEURON	2	A					0,534										1,000					1,000		
	2	ALSO	1,000			0,534	0,310															0,534		1,000
	1	CAN											1,000							0,310				0,534
	1	CLEVER																						
	1	DOG																						
	2	HAVE	1,534	1,000			0,192										0,534					0,310		
	1	HEAD																						
	2	I	0,844	0,534			0,126	2,000									0,310					0,192		
	4	IS		1,000		0,310										1,534						0,534		2,534
	5	IT		0,534	1,000	0,192			0,085		2,000		0,534	1,000	1,000	0,310		0,126	0,192	0,726	0,310		0,534	1,154
	1	JUMP																		0,534				1,000
	1	LEARNS																		1,000				
	1	LIKES							0,126									0,192	0,310		0,534		1,000	
	2	LOVELY																						
	3	MONKEY									2,000					0,534						0,310		0,534
	3	MY							1,000		1,067					0,310	2,000					0,192		0,310
	1	ON							0,534									1,000						
	2	QUICKLY																						
	1	SIT							0,310									0,534	1,000					
	2	SMALL					1,000																	
	1	TO							0,192									0,310	0,534		1,000			
	4	VERY				1,000										1,000				1,000		1,000		

COMPUTATION OF WEIGHTS FOR CREATED SYNAPSES

$$w_{S,\widehat{S}} = \frac{\eta_S \cdot \delta_{S,\widehat{S}} \cdot \theta_{\widehat{S}}}{\eta_S + (\eta_S - 1) \cdot \delta_{S,\widehat{S}}} \qquad (2)$$

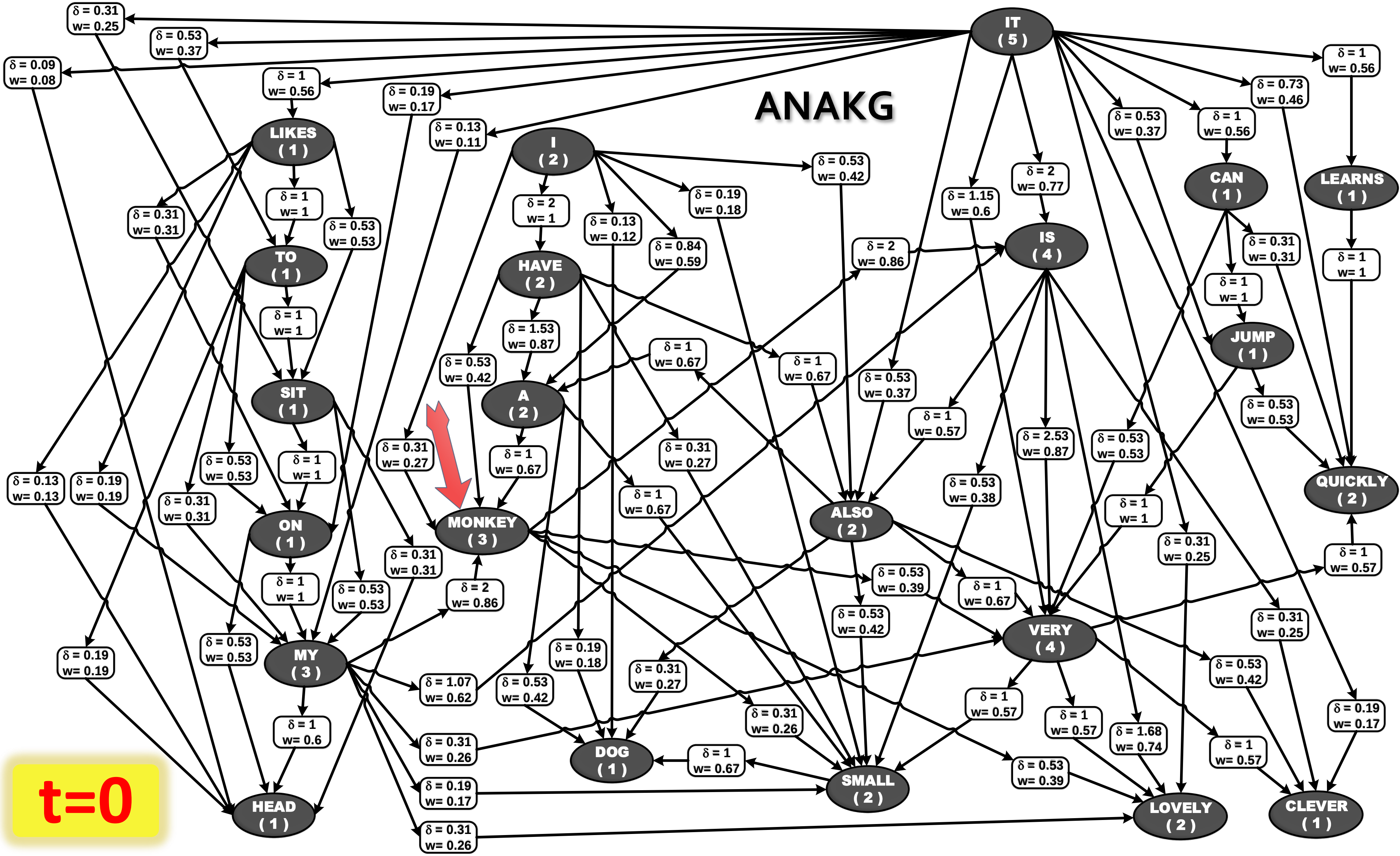
		POSTSYNAPTIC AS-NEURON																					
	w	A	ALSO	CAN	CLEVER	DOG	HAVE	HEAD	I	IS	IT	JUMP	LEARNS	LIKES	LOVELY	MONKEY	MY	ON	QUICKLY	SIT	SMALL	TO	VERY
PRESYNAPTIC AS-NEURON	A					0,421										0,667					0,667		
	ALSO	0,667			0,421	0,269															0,421		0,667
	CAN											1,000							0,310				0,534
	CLEVER																						
	DOG																						
	HAVE	0,868	0,667			0,175										0,421					0,269		
	HEAD																						
	I	0,593	0,421			0,118	1,000									0,269					0,175		
	IS		0,571		0,252										0,713						0,381		0,874
	IT		0,374	0,556	0,167			0,080		0,769		0,374	0,556	0,556	0,248		0,114	0,167	0,459	0,248		0,374	0,600
	JUMP																		0,534				1,000
	LEARNS																		1,000				
	LIKES							0,126									0,192	0,310		0,534		1,000	
	LOVELY																						
	MONKEY									0,857					0,394						0,257		0,394
	MY							0,600		0,624					0,257	0,857					0,170		0,257
	ON							0,534									1,000						
	QUICKLY																						
	SIT							0,310									0,534	1,000					
	SMALL					0,667																	
	TO							0,192									0,310	0,534		1,000			
	VERY				0,571										0,571				0,571		0,571		

ASSOCIATIVE NEURAL GRAPH ANAKG-2
is ready for external stimulations

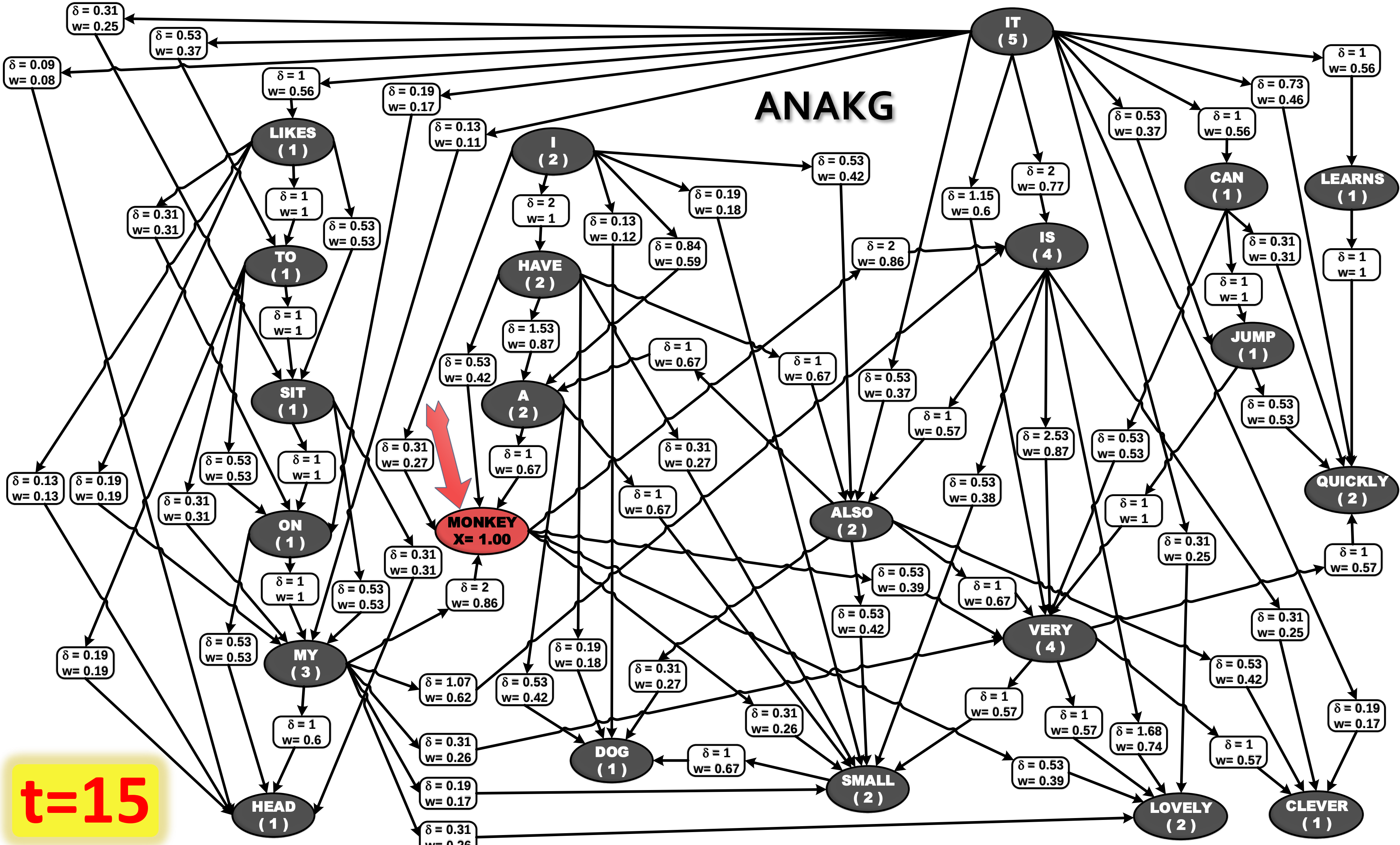


ASSOCIATIVE NEURAL GRAPH ANAKG-2

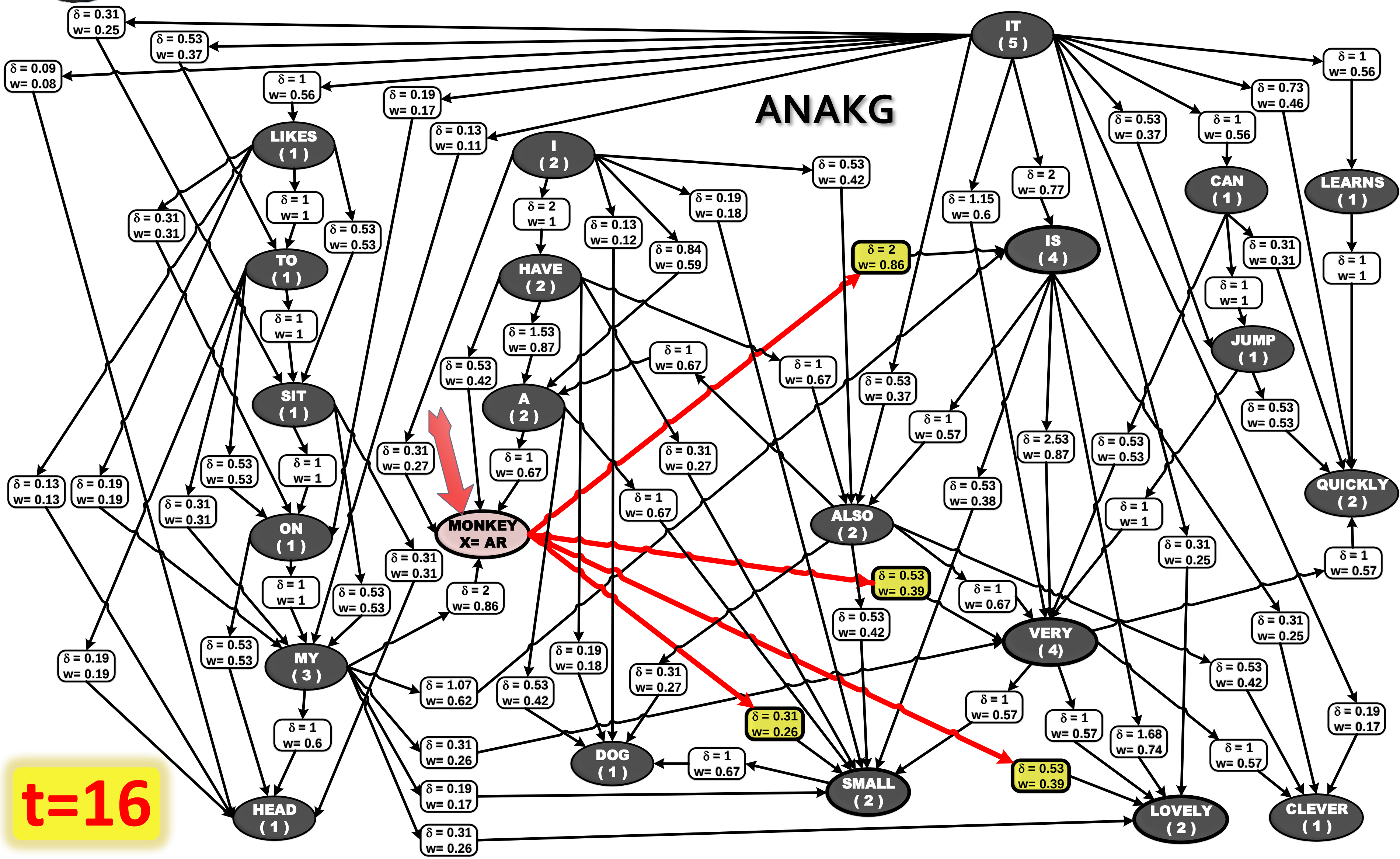
Neuron MONKEY is being stimulated.



ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron MONKEY is activated.

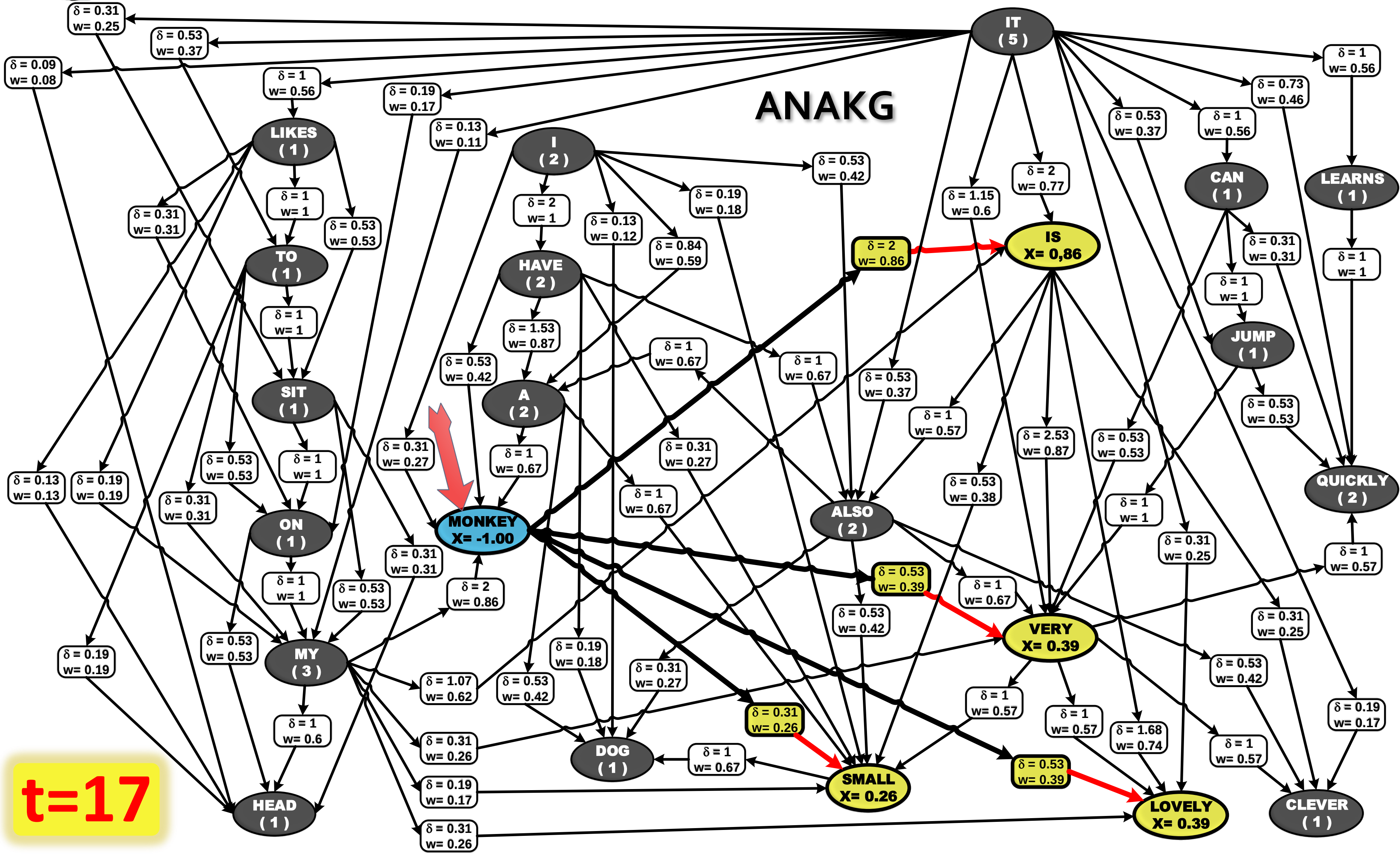


ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron MONKEY stimulates synapses.



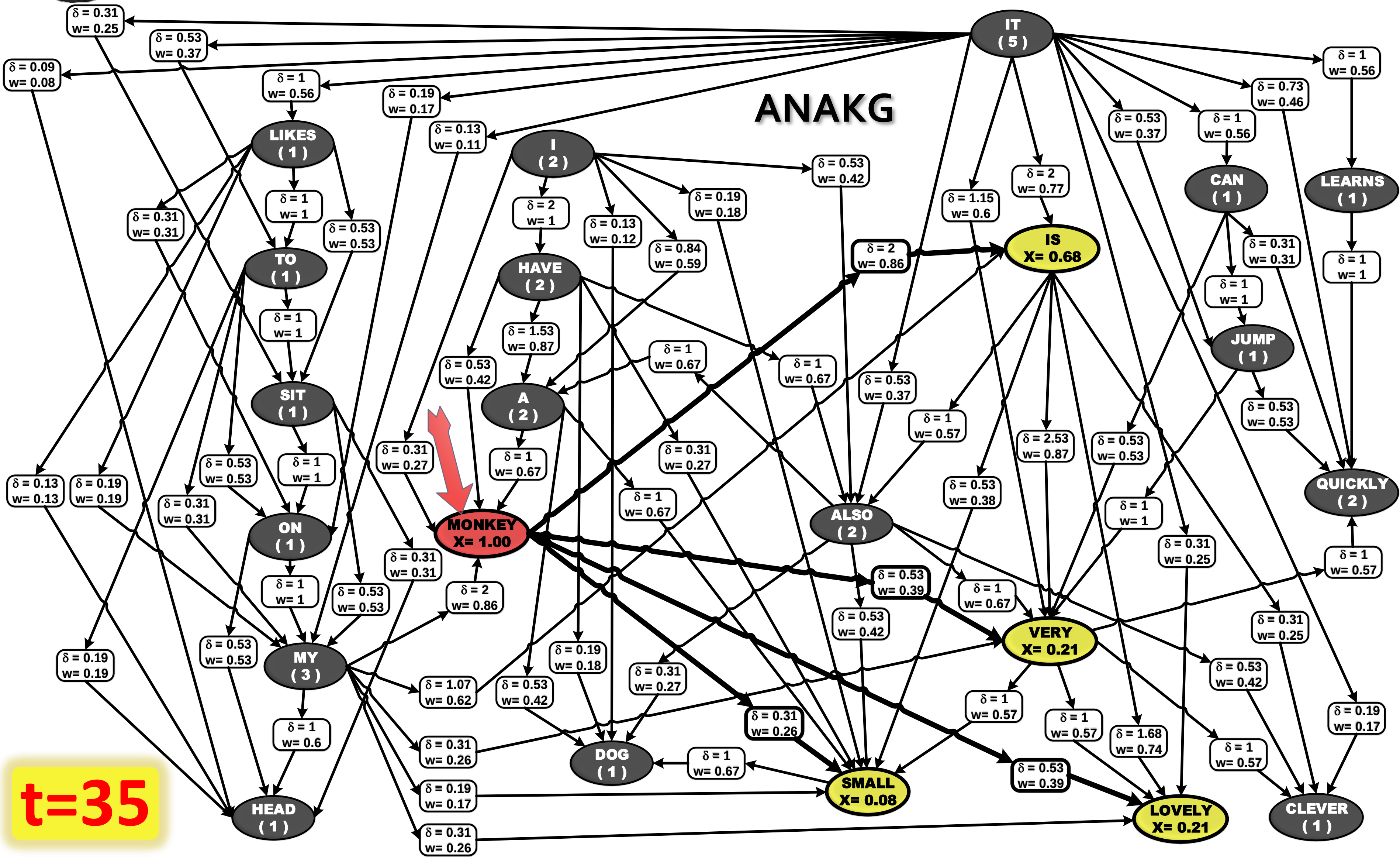
ASSOCIATIVE NEURAL GRAPH ANAKG

Neuron MONKEY stimulates connected neurons.



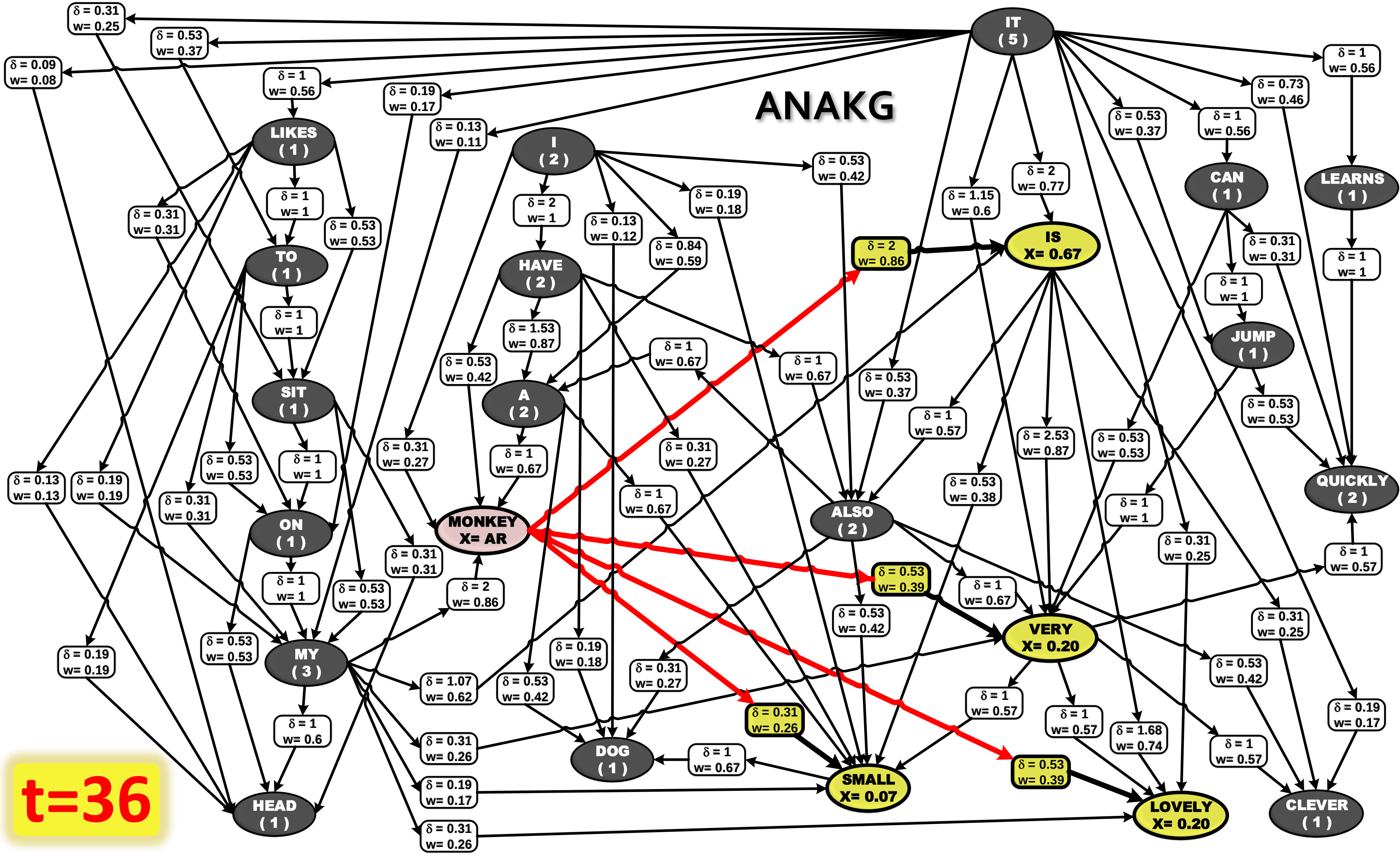
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron MONKEY is stimulated the 2nd time.



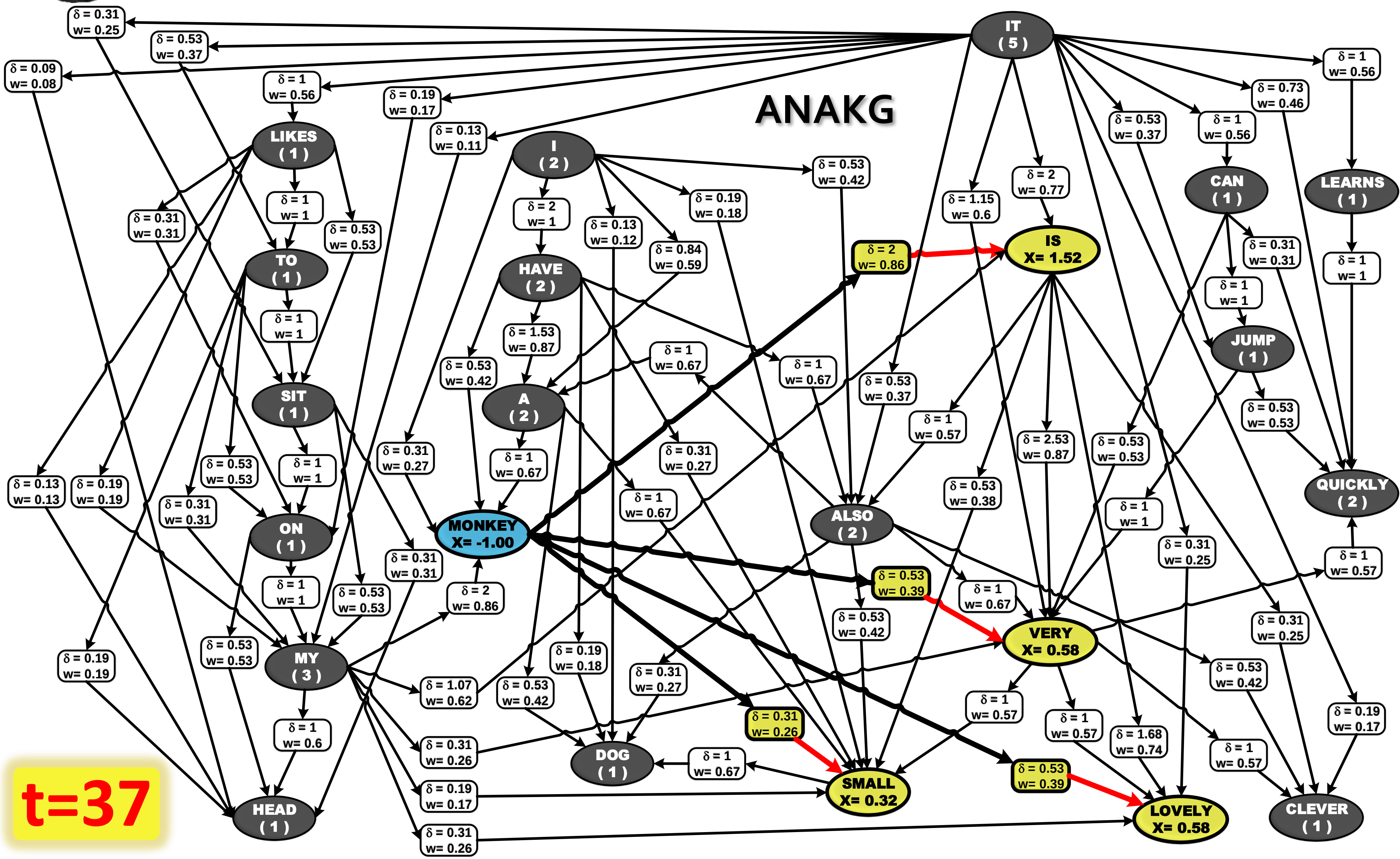
t=35

ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron MONKEY stimulates synapses.



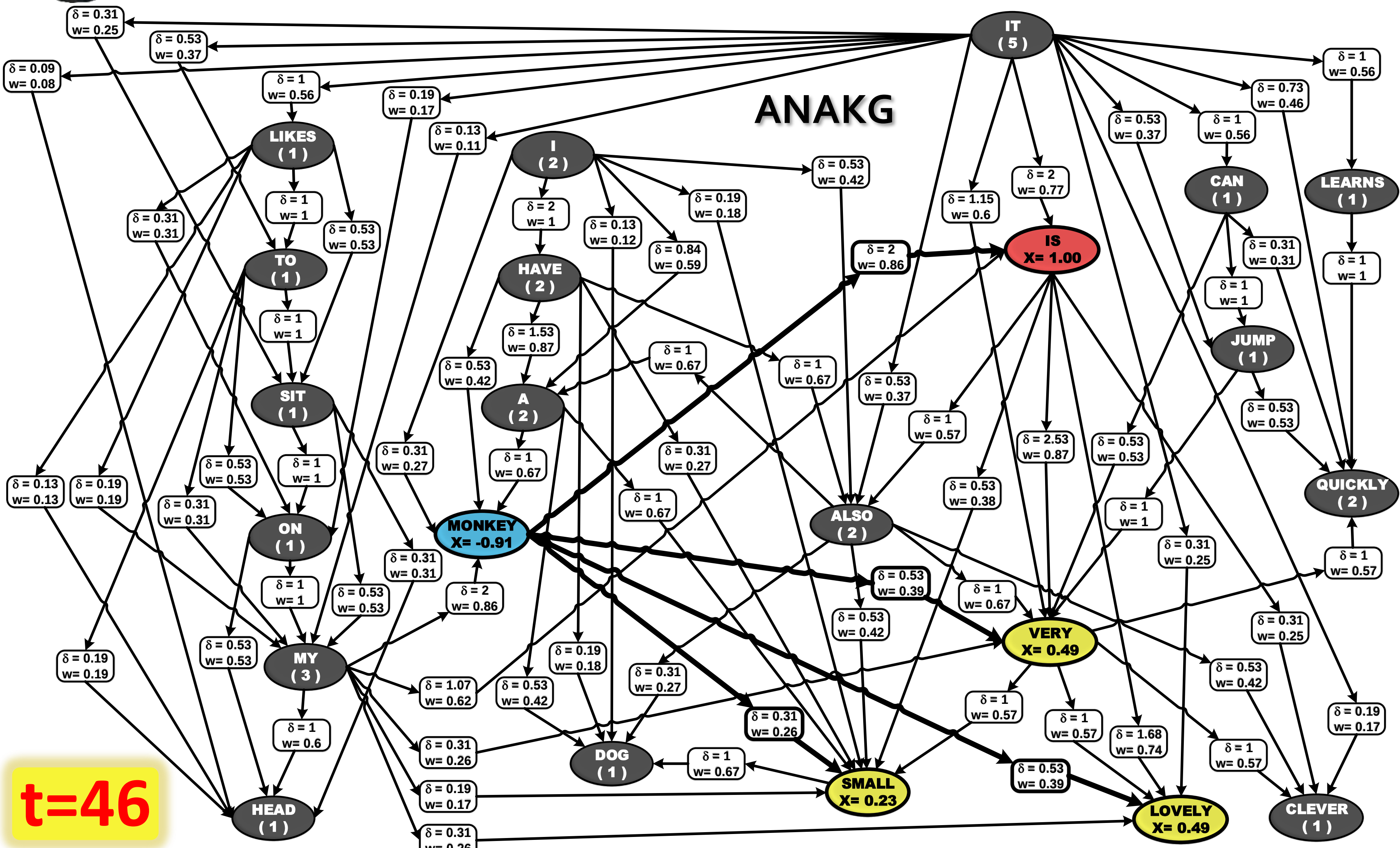
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron MONKEY stimulates connected neurons.

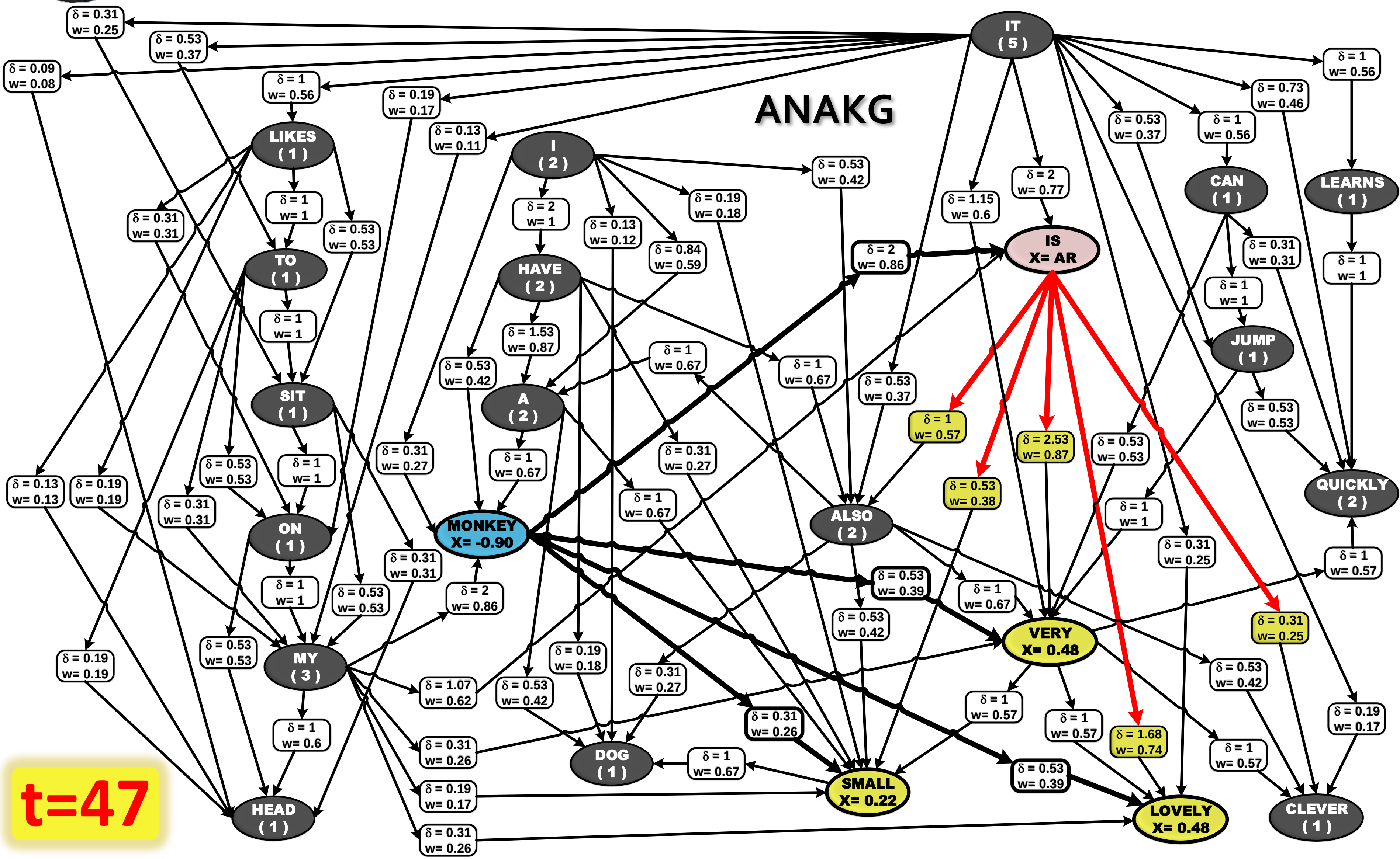


ASSOCIATIVE NEURAL GRAPH ANAKG-2

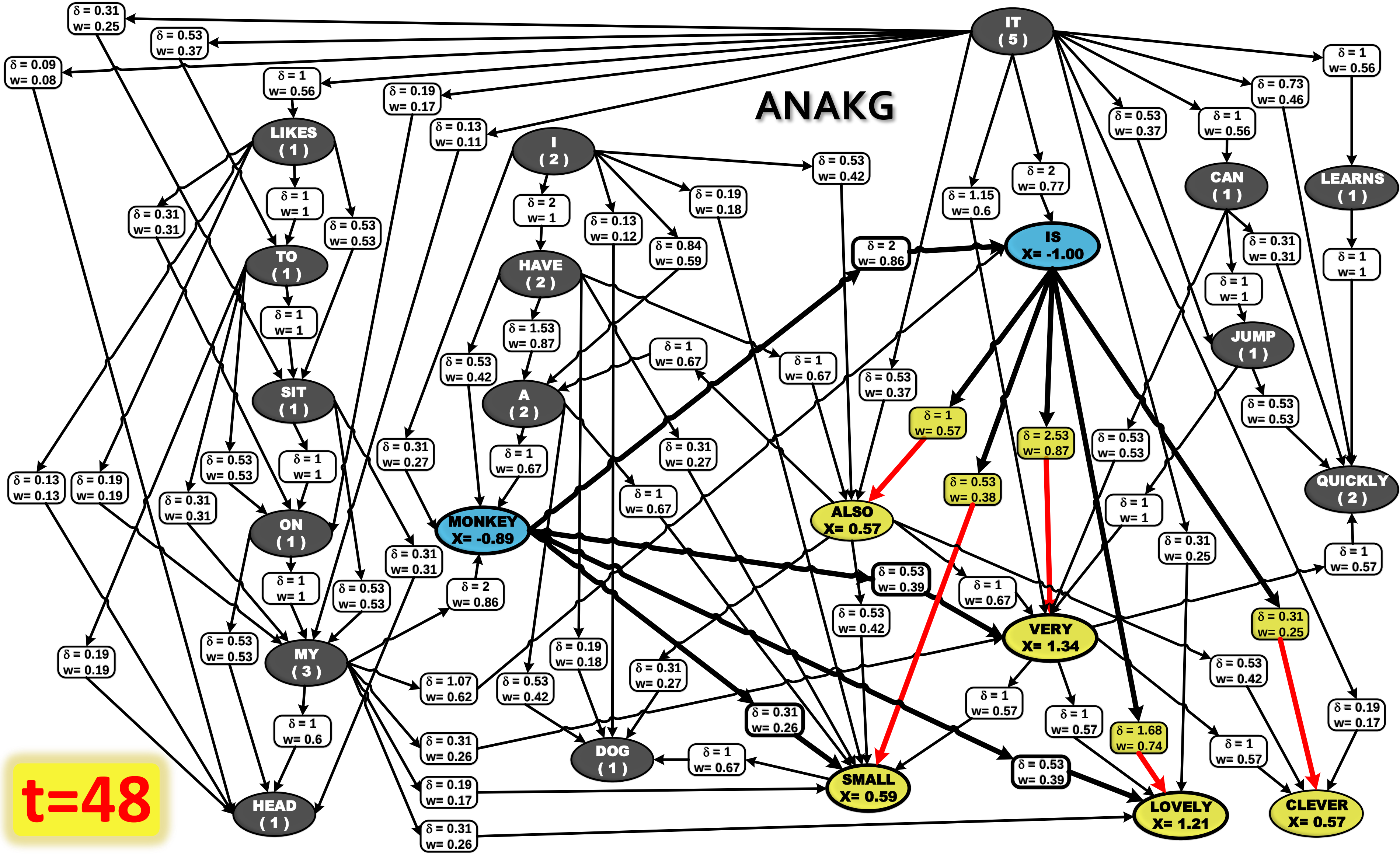
Neuron IS is activated as a result of the stimulations.



ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron IS stimulates synapses.

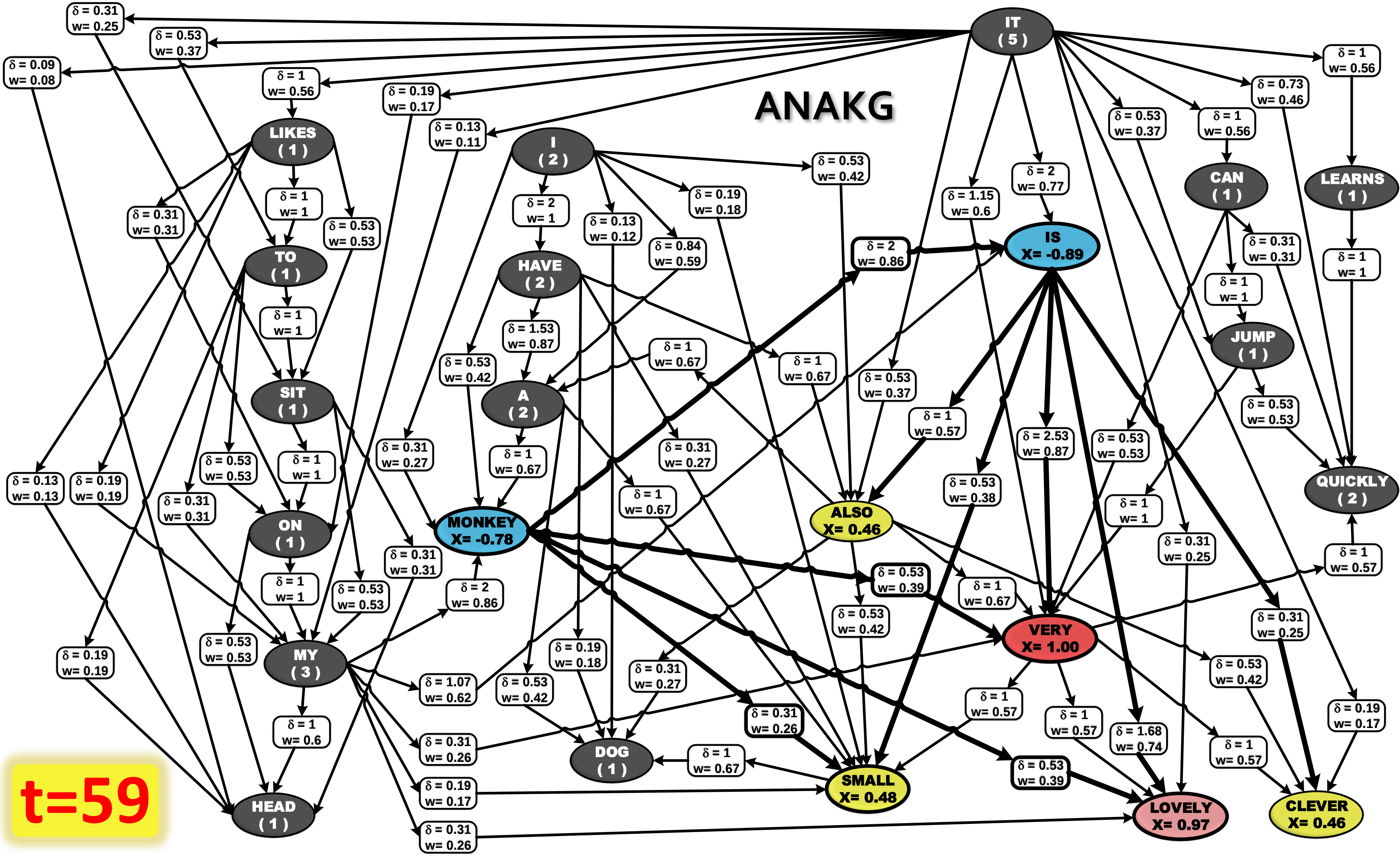


ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron IS stimulates connected neurons.



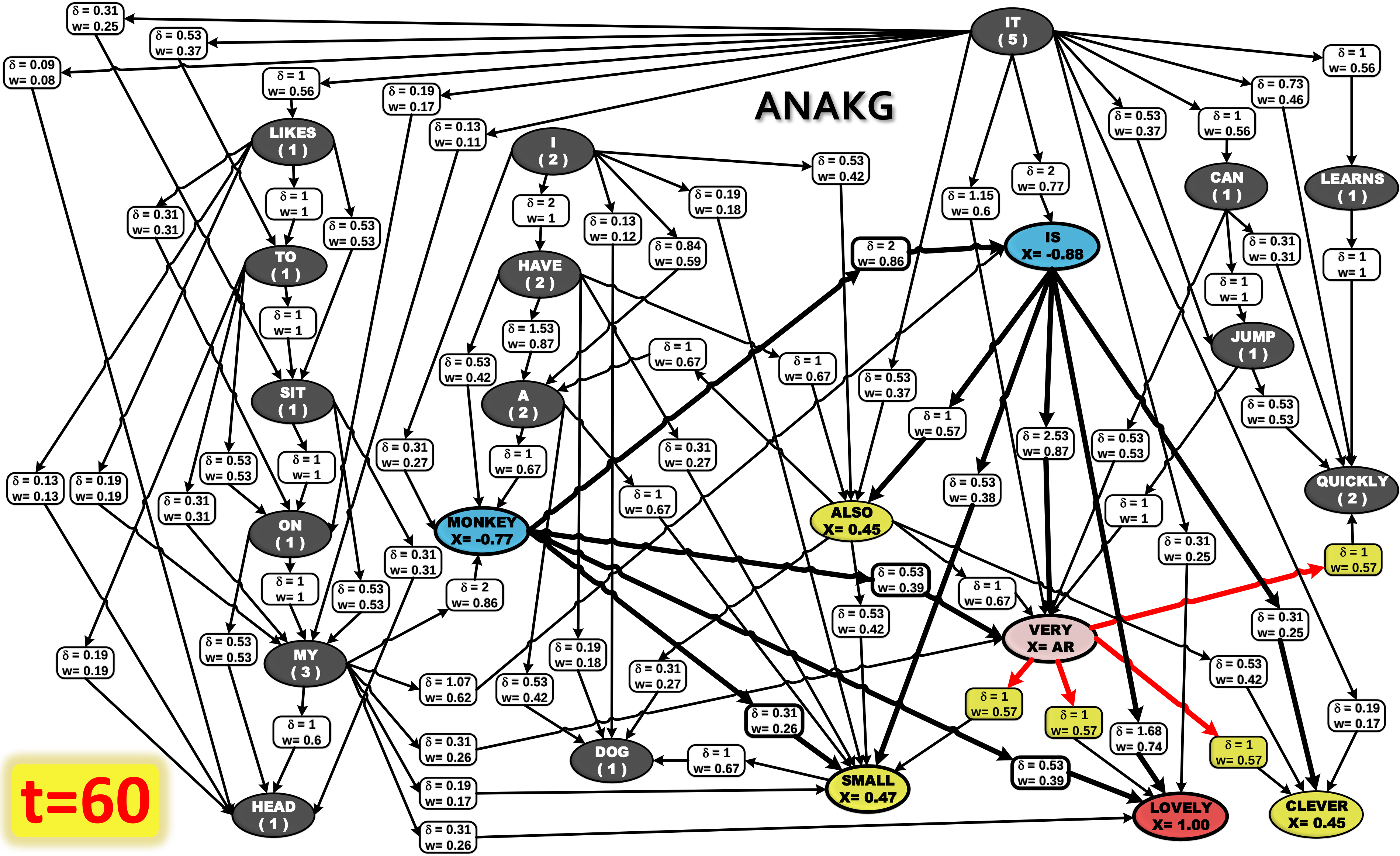
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron VERY is activated as a result of the stimulations



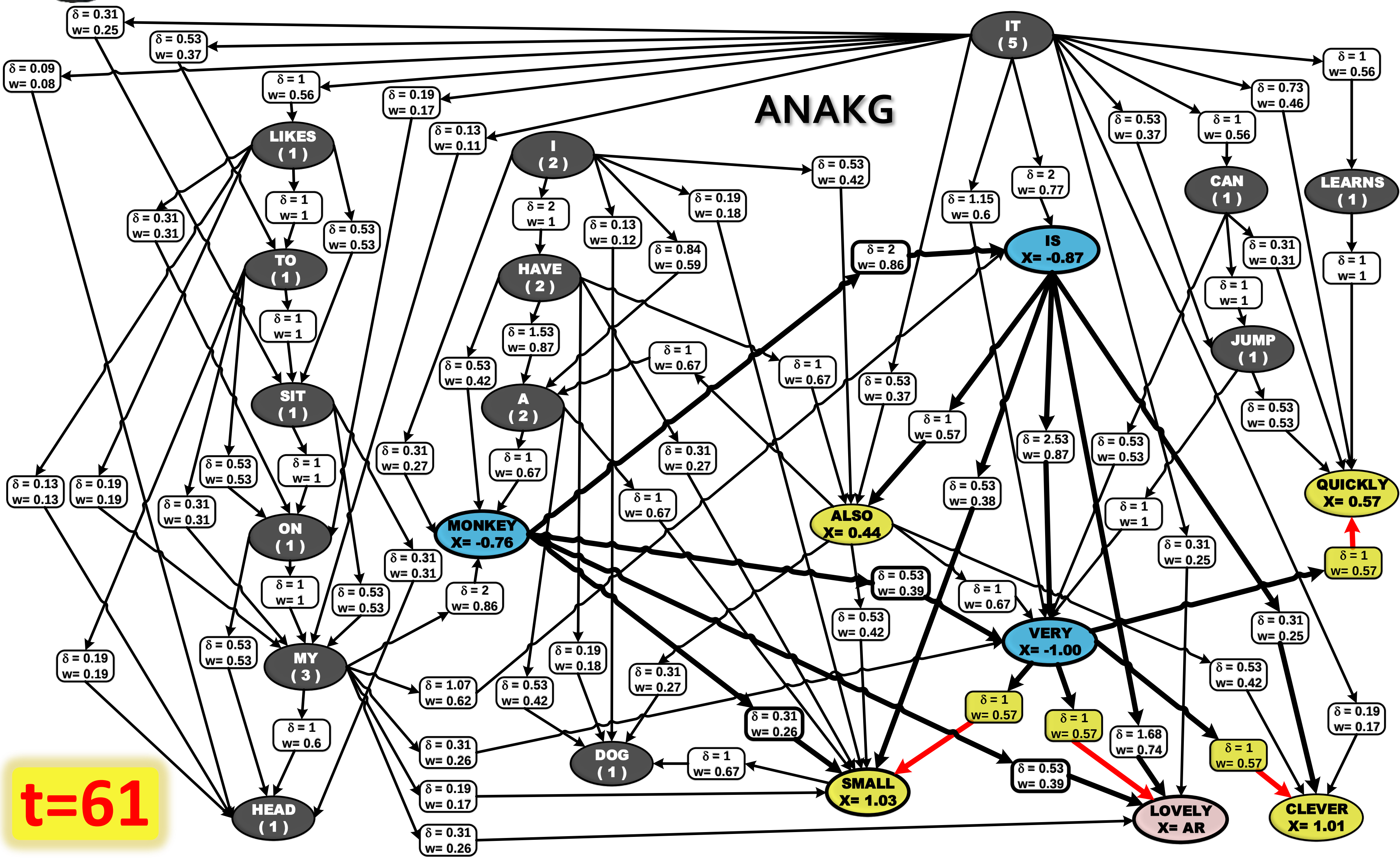
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron IS is activated as a result of the stimulations



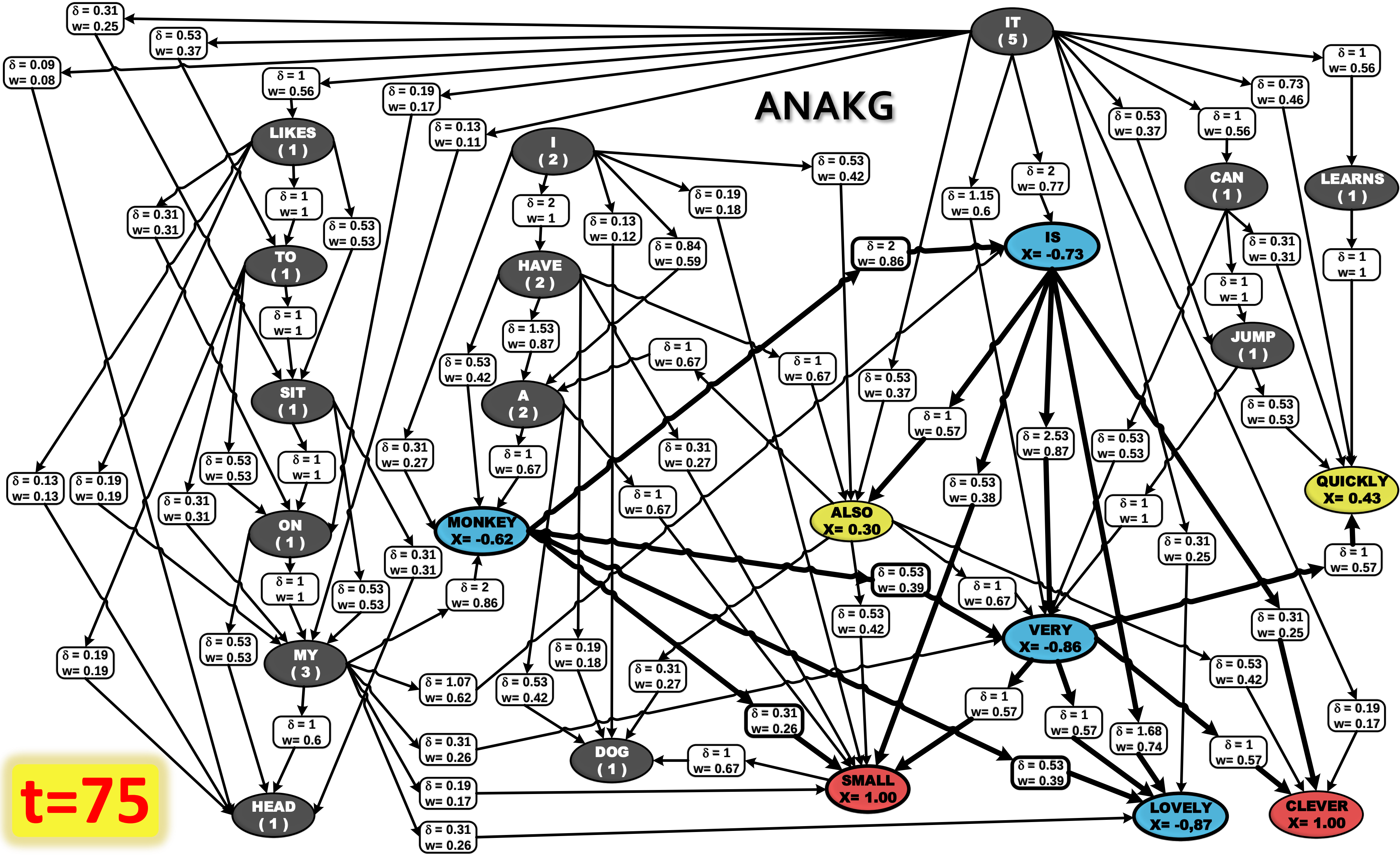
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron VERY stimulates connected neurons

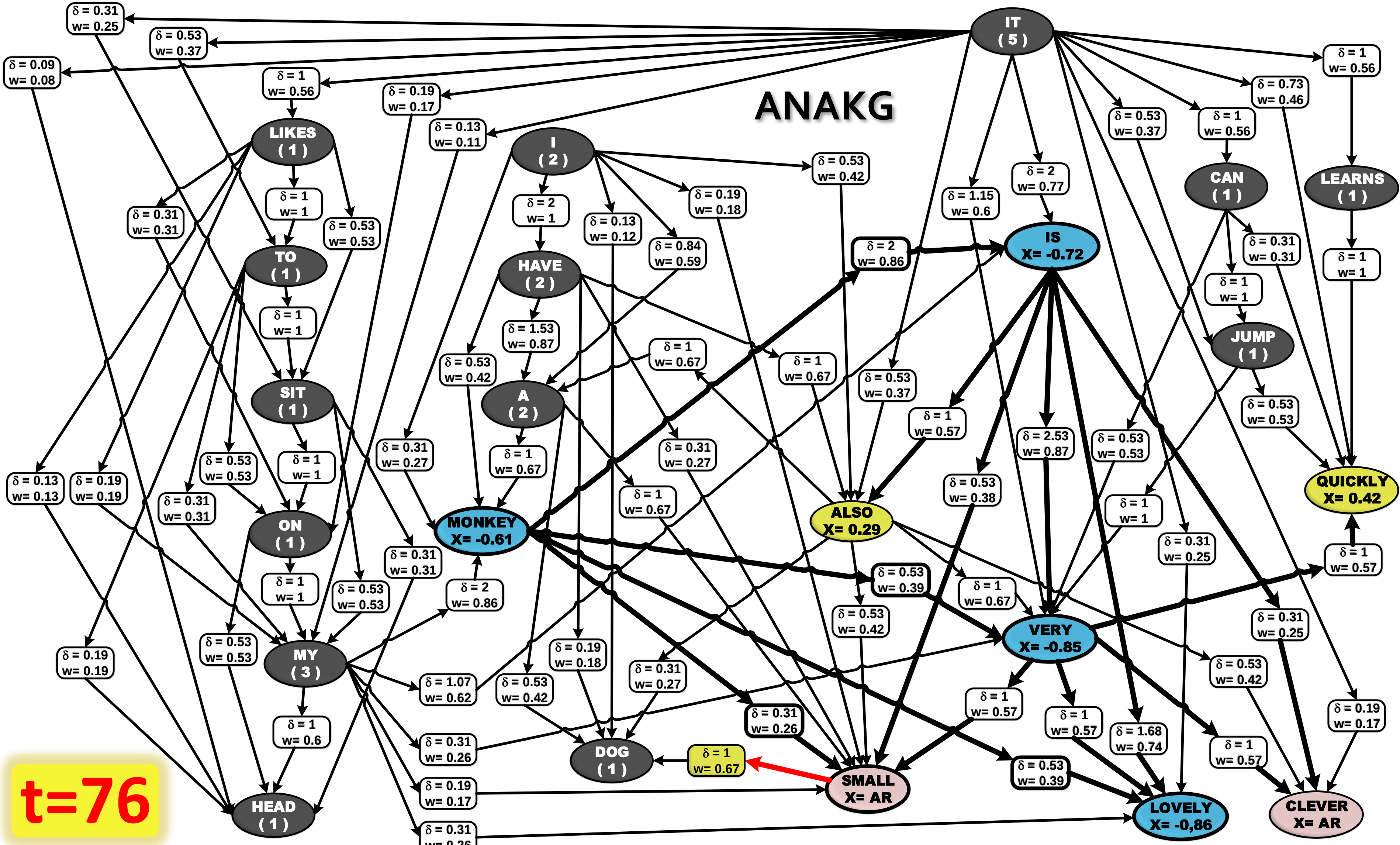


t=61

ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neurons SMALL and VERY are activated.

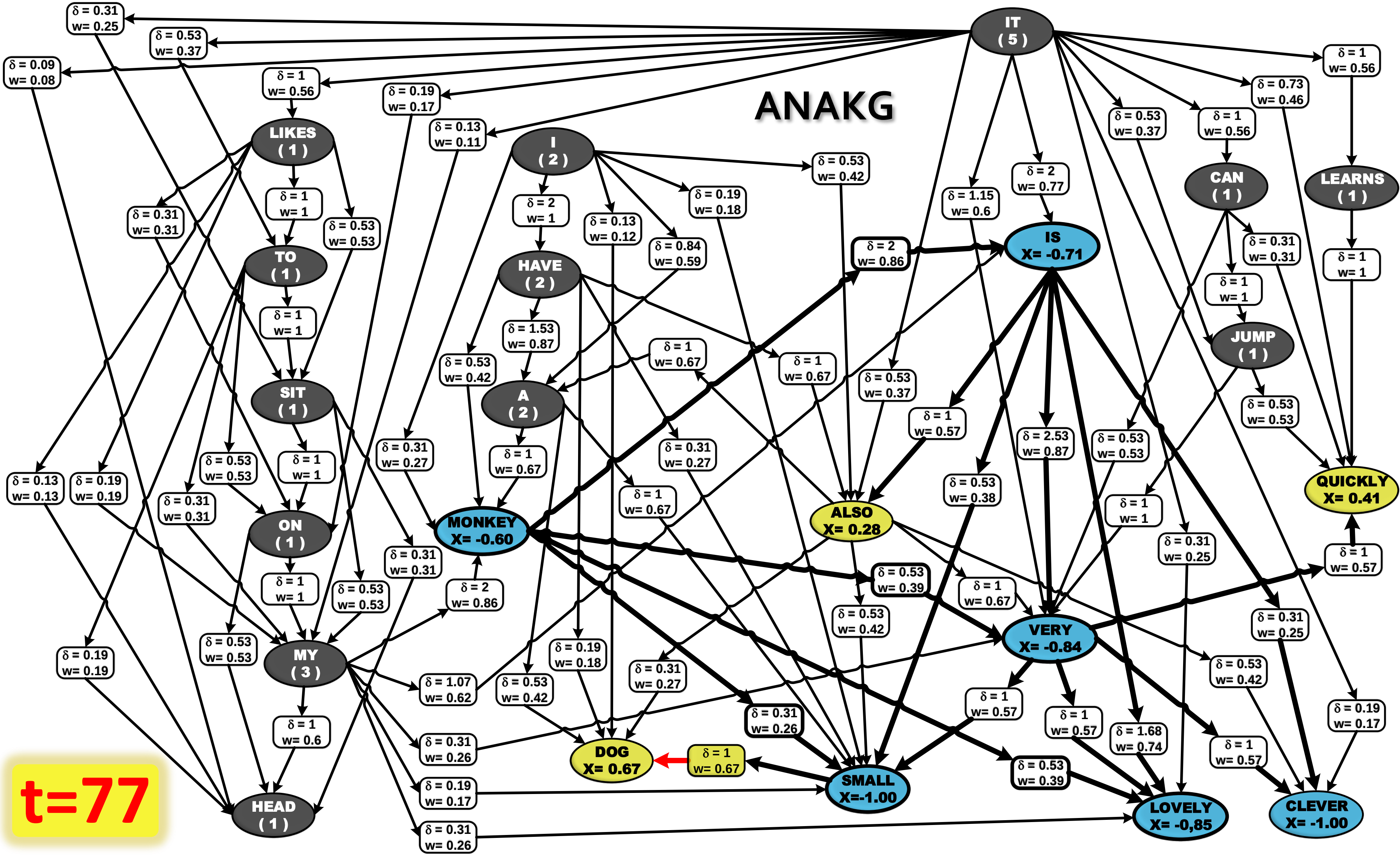


ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron SMALL stimulates a synapsis.

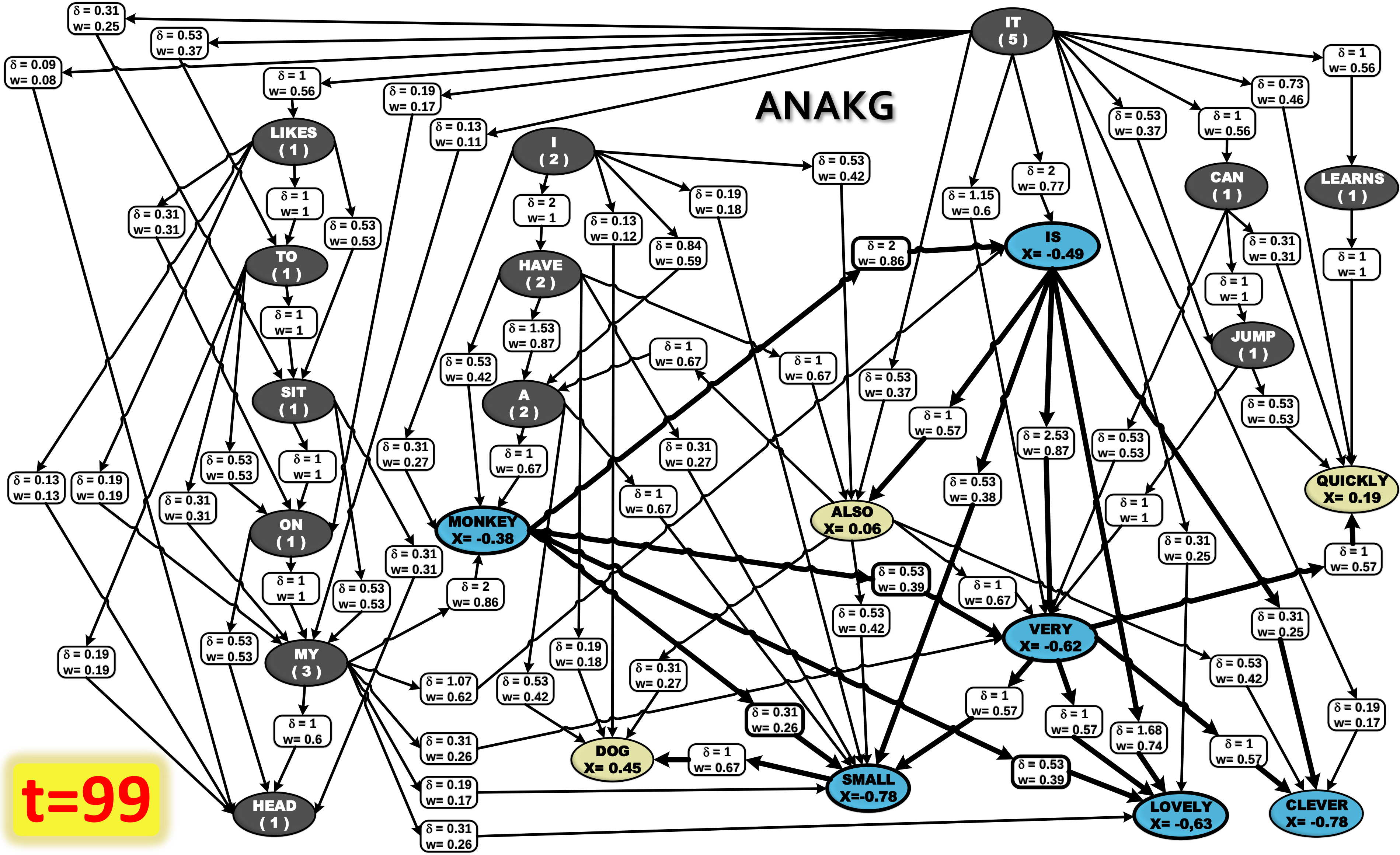


ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron SMALL stimulates a connected neuron



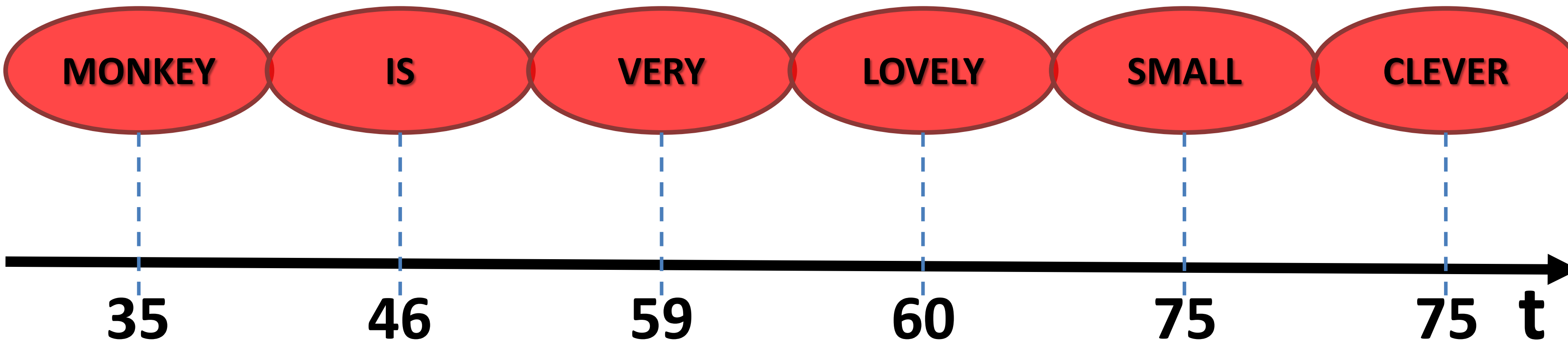
All neurons are relaxing, refracting, and returning back to their resting states.



t=99

ASSOCIATIVE NEURAL GRAPH ANAKG-2
What answer we got?

What answer returned this associative neural graph for external stimulation of neuron MONKEY?



I cannot agree more!

What do you think about me?

Has the created associative neural graph gained any knowledge about this MONKEY?

ASSOCIATIVE NEURAL GRAPH ANAKG-2
CONCLUSIONS AND REMARKS

"I have a monkey. My monkey is very small. It is very lovely. It likes to sit on my head. It can jump very quickly. It is also very clever. It learns quickly. My monkey is lovely. I have also a small dog."

The training sequence set did not include the summary about this monkey we got:

Monkey is very lovely, small, clever.

CONCLUSION:

The developed Associative Neural Graph gained some knowledge about this monkey and generalized training sentences.

GENERAL CONCLUSIONS ABOUT ASSOCIATIVE NEURAL GRAPHS

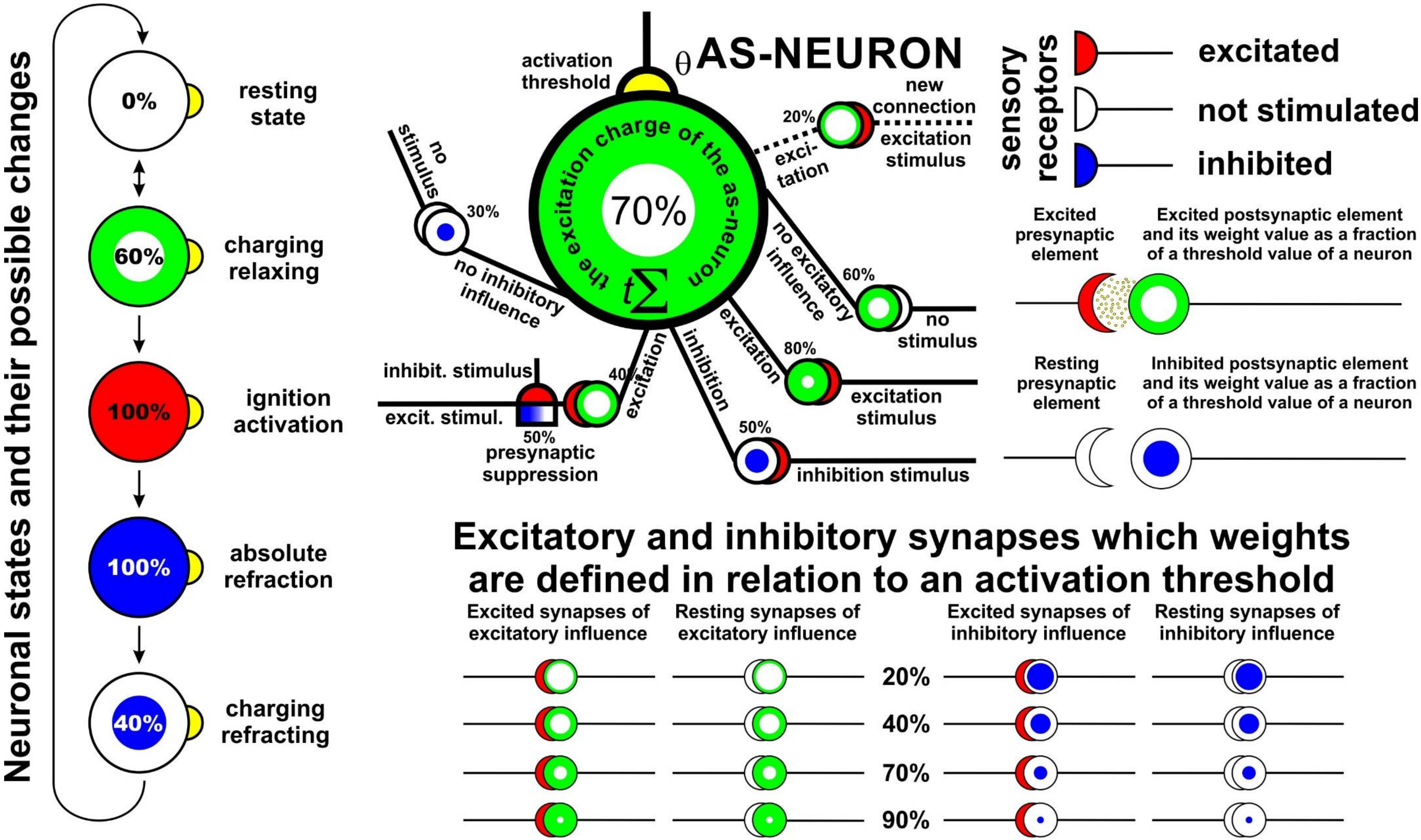
- ✓ **Can form, model, and represent knowledge.**
- ✓ **Use plastic mechanisms to create a structure that reproduces relations between objects.**
- ✓ **Construction and adaptation is very fast and easy.**
- ✓ **We can recall artificial associations for reconstruction of training sequences or generalization about them.**
- ✓ **The associative answer depends on a given context for recalling:**
  - **Longer contexts will usually reproduce training sequences.**
  - **Shorter contexts will generalize or return the most frequent training sequences.**
- ✓ **We can use them for data mining, knowledge exploration, formation, and discovery.**

POSSIBLE IMPLEMENTATIONS OF ASSOCIATIVE NEURAL GRAPHS

- ✓ Data mining, knowledge exploration and discovery, frequent pattern exploration and analysis, concluding…
- ✓ Researching and modeling of associative processes in biological nervous systems.
- ✓ Proof-reading of texts and their semi-automatic correction.
- ✓ Supporting automatic translation when associating phrases.
- ✓ Aggregation and consolidation of many facts, rules.
- ✓ Big data can be transformed on the fly into these associative neural graph structures.
- ✓ Can be useful for linguistic chatbot constructions.
- ✓ Can be used as an emergent cognitive architecture.
- ✓ Can help to develop intelligent artificial associative systems.

AS-NEURONS NOTATIONS

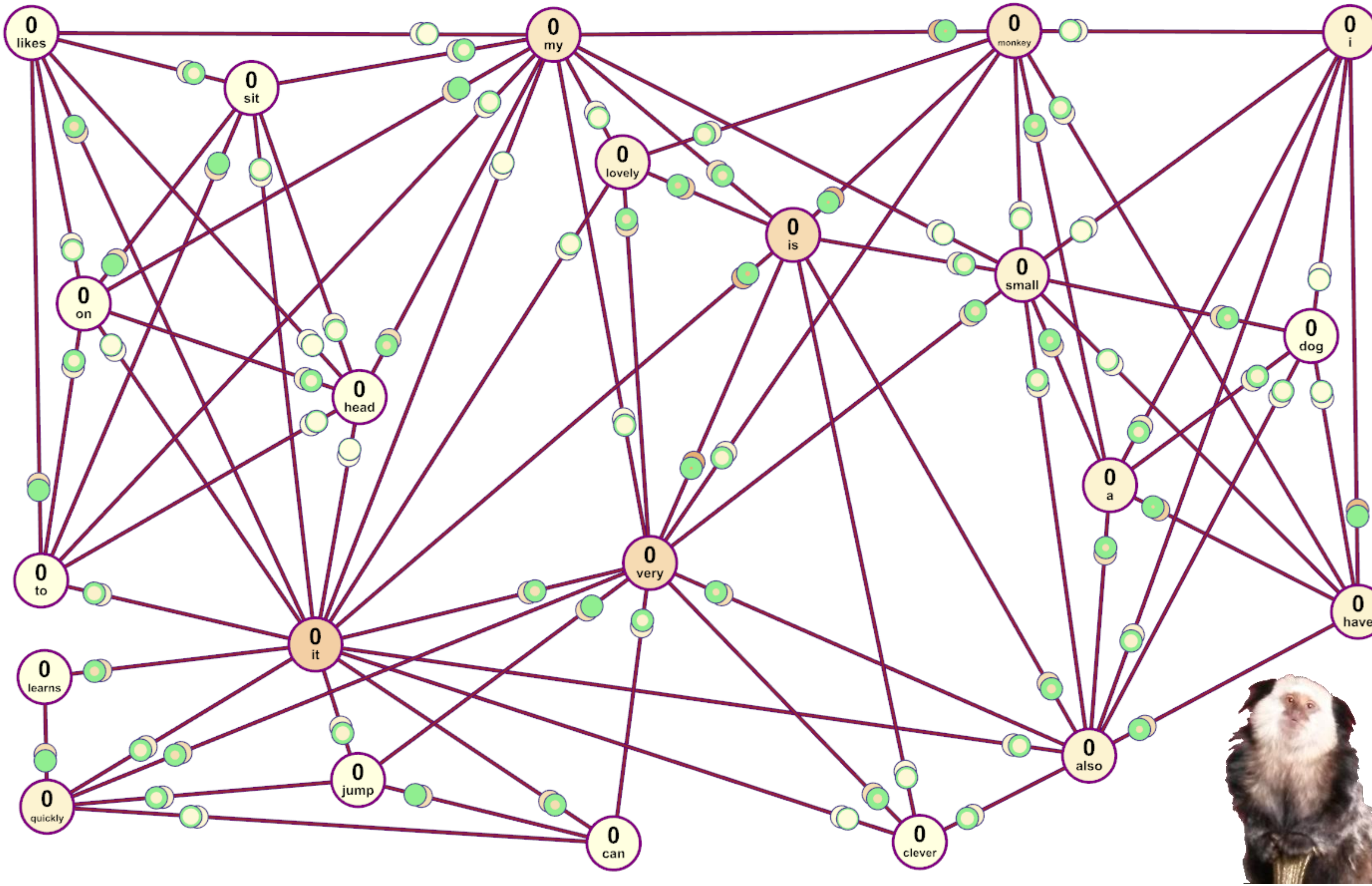
As-neurons change their internal states on stimuli and time lapse.



Weight values are notated as a fraction of a threshold value.

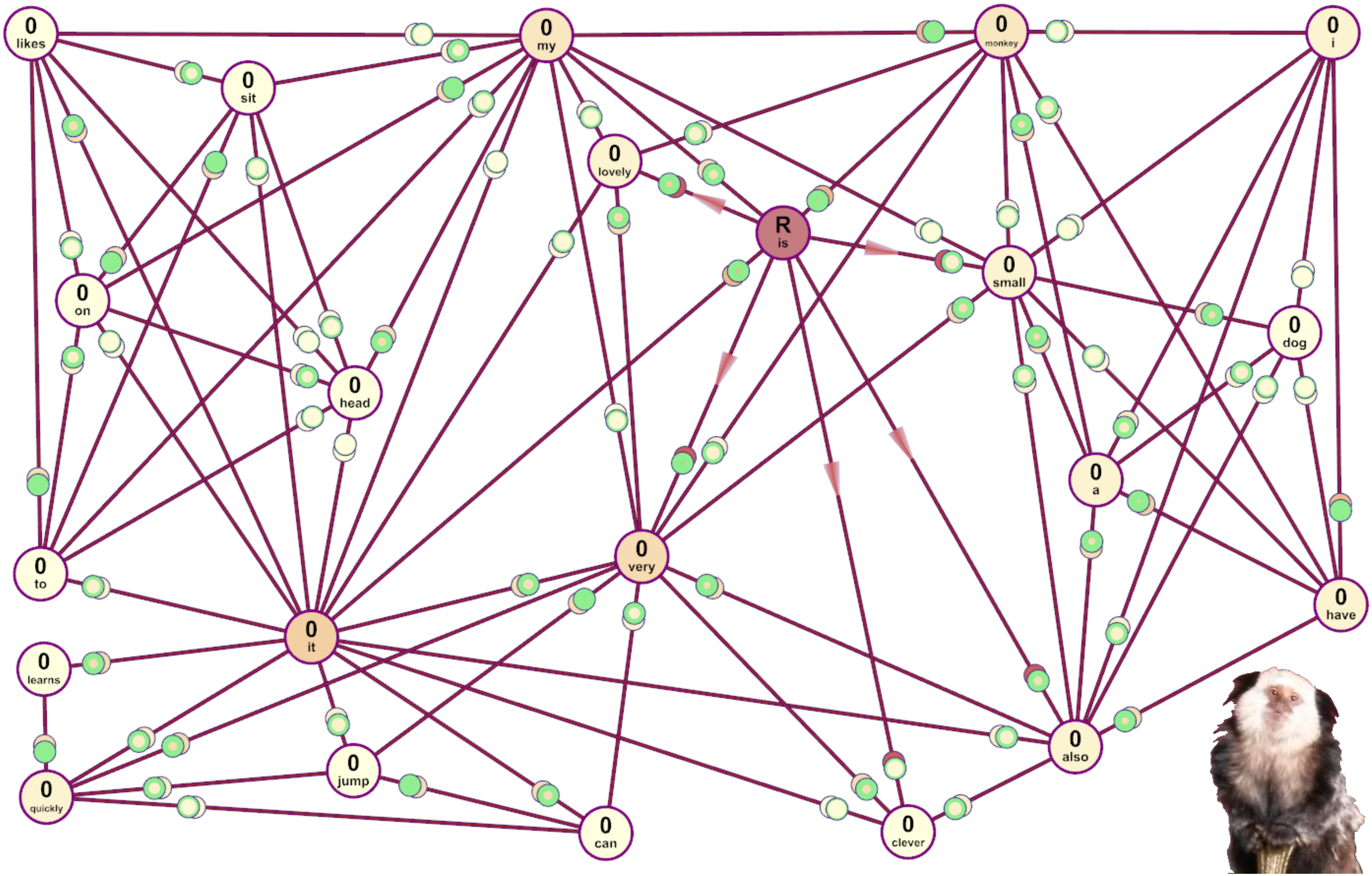
ASSOCIATIVE NEURAL GRAPHS

ANAKG-2 for training sequence set MONKEY in this notation.



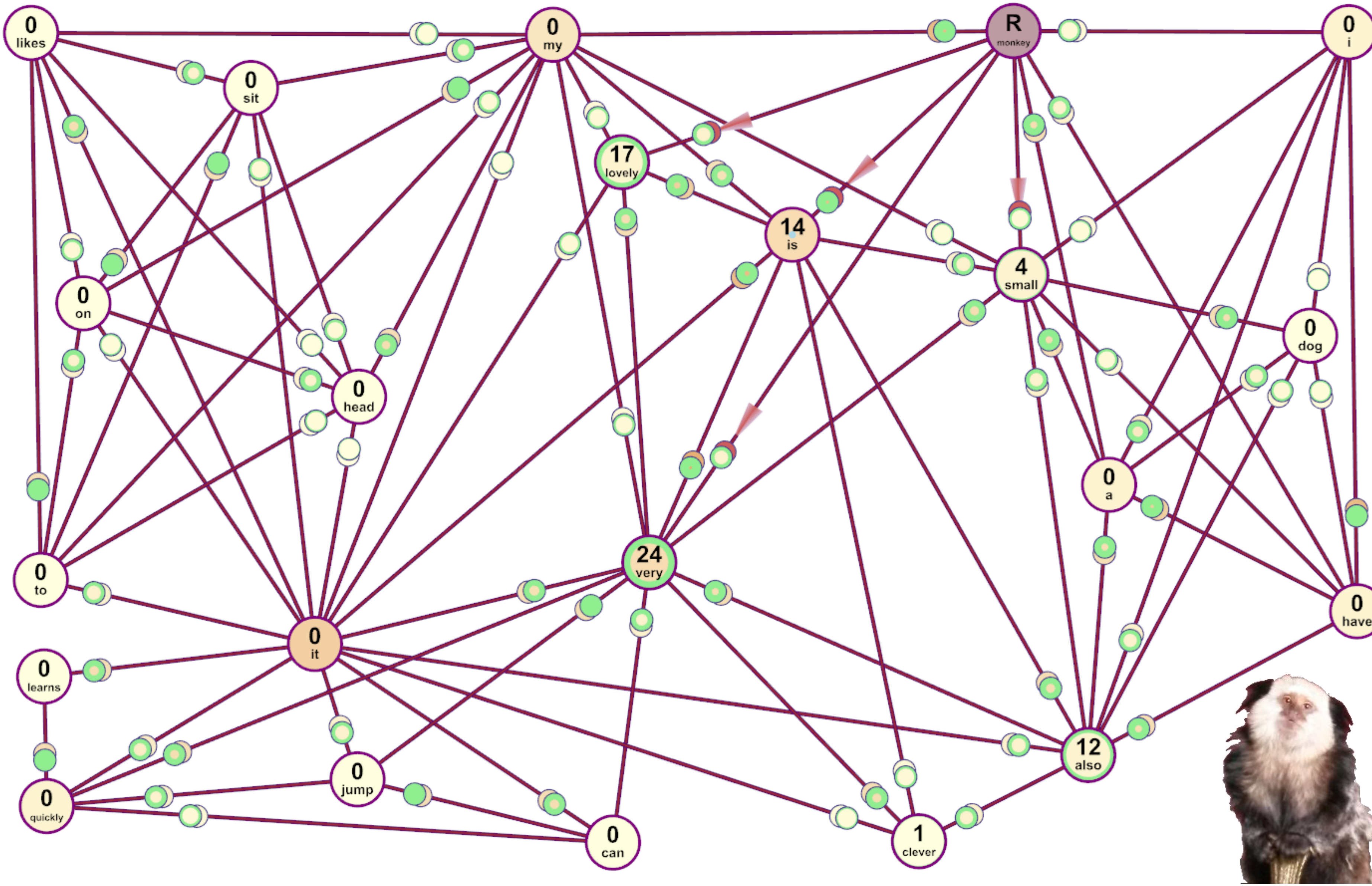
ASSOCIATIVE NEURAL GRAPHS

Activation of neuron MONKEY and stimulation of connected neurons.



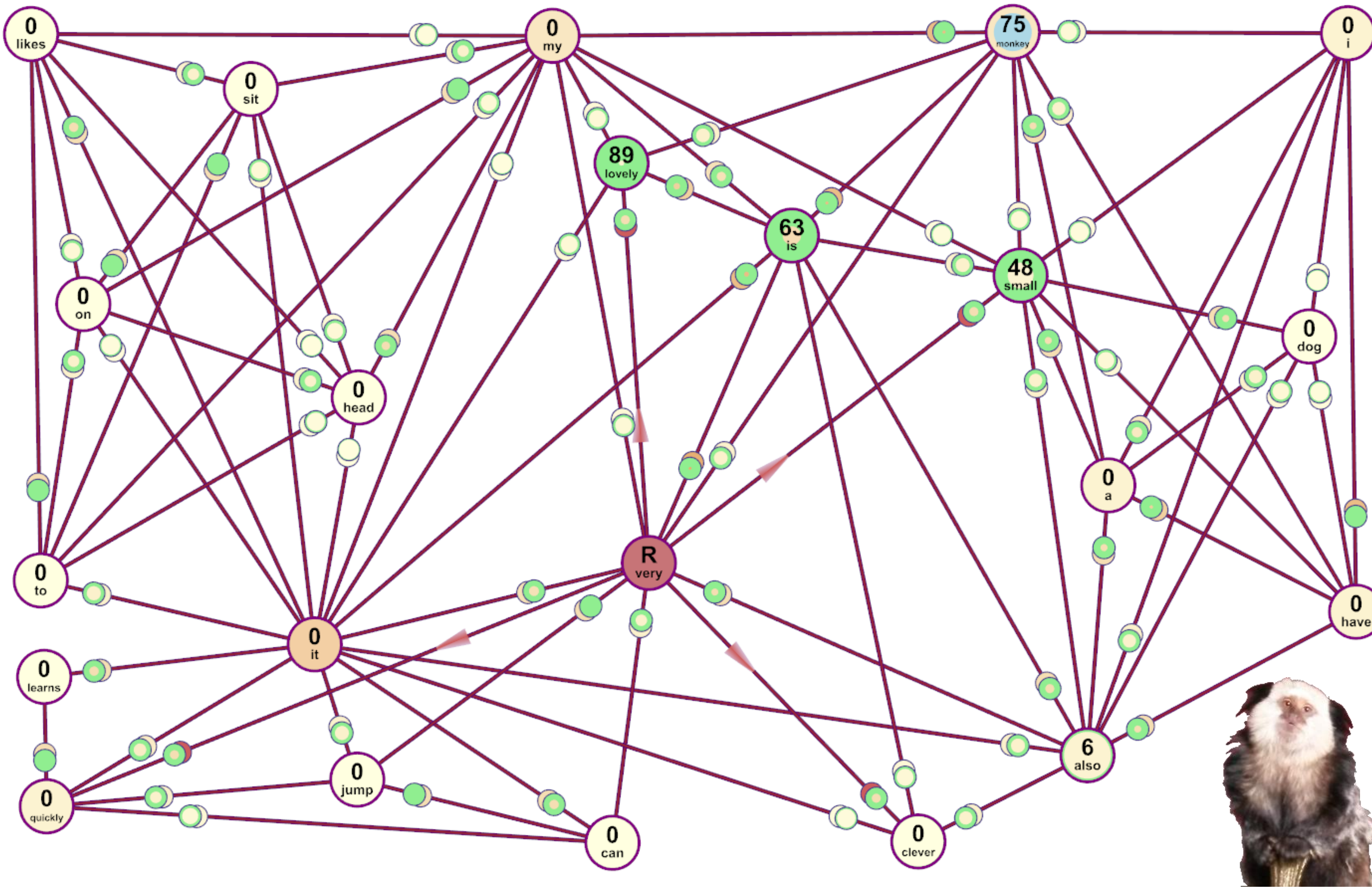
ASSOCIATIVE NEURAL GRAPHS

ANAKG-2 is producing reaction on: „What **is** this **monkey** like?”



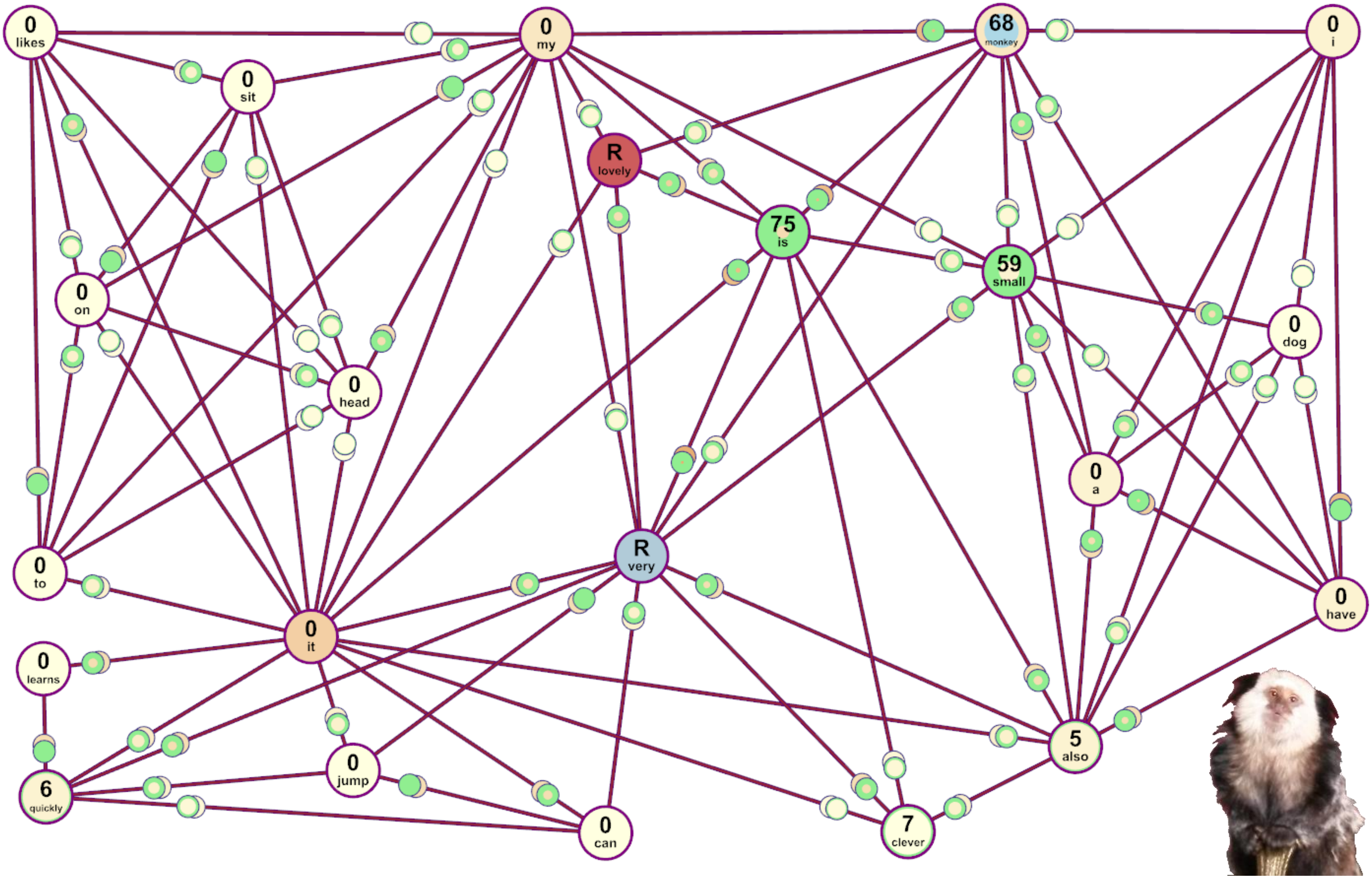
ASSOCIATIVE NEURAL GRAPHS

ANAKG-2 is gradually producing answer: IS – MONKEY – VERY – …



ASSOCIATIVE NEURAL GRAPHS

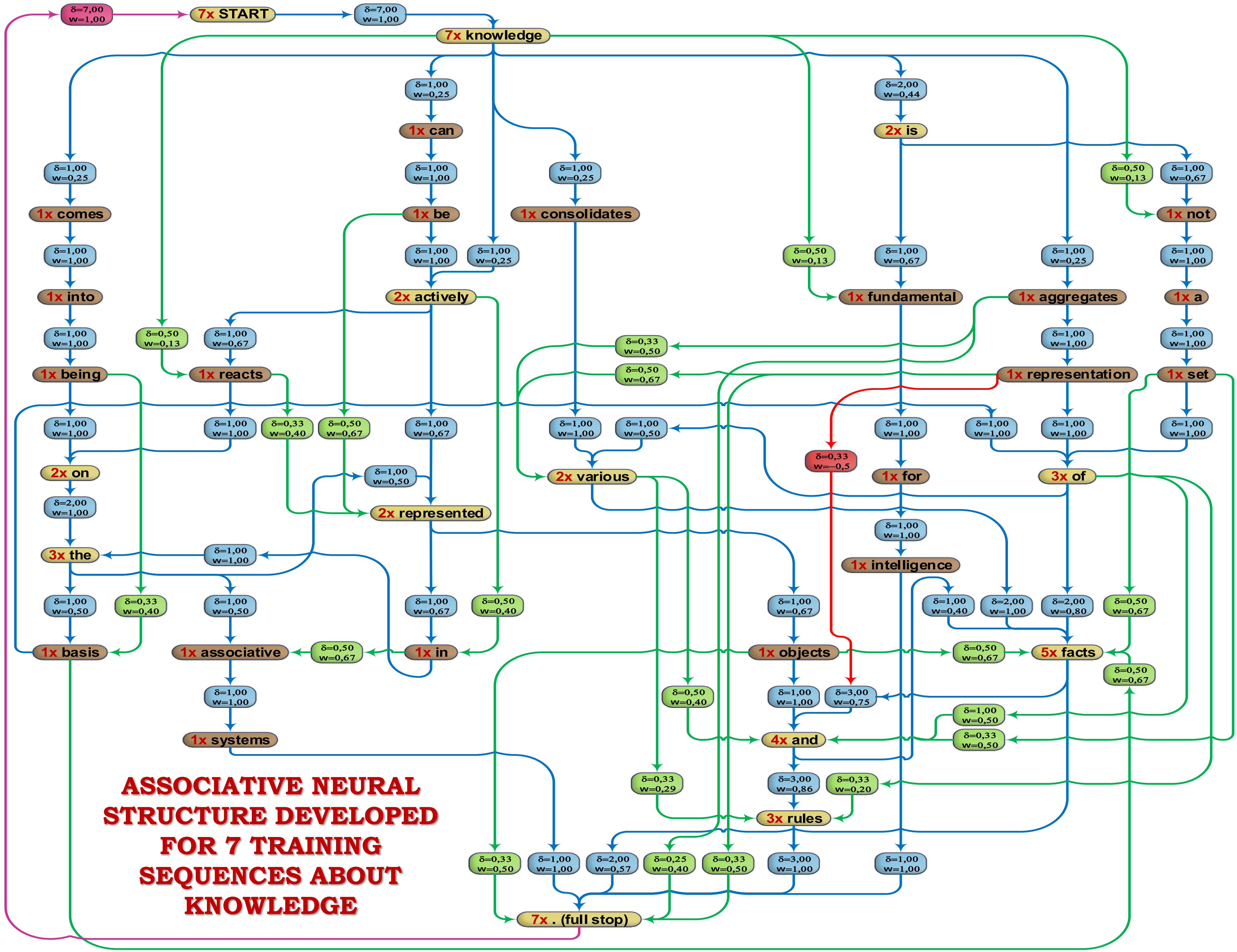
ANAKG-2 is gradually producing answer: IS – MONKEY – VERY – LOVELY …



7 TRAINING SEQUENCES ABOUT KNOWLEDGE

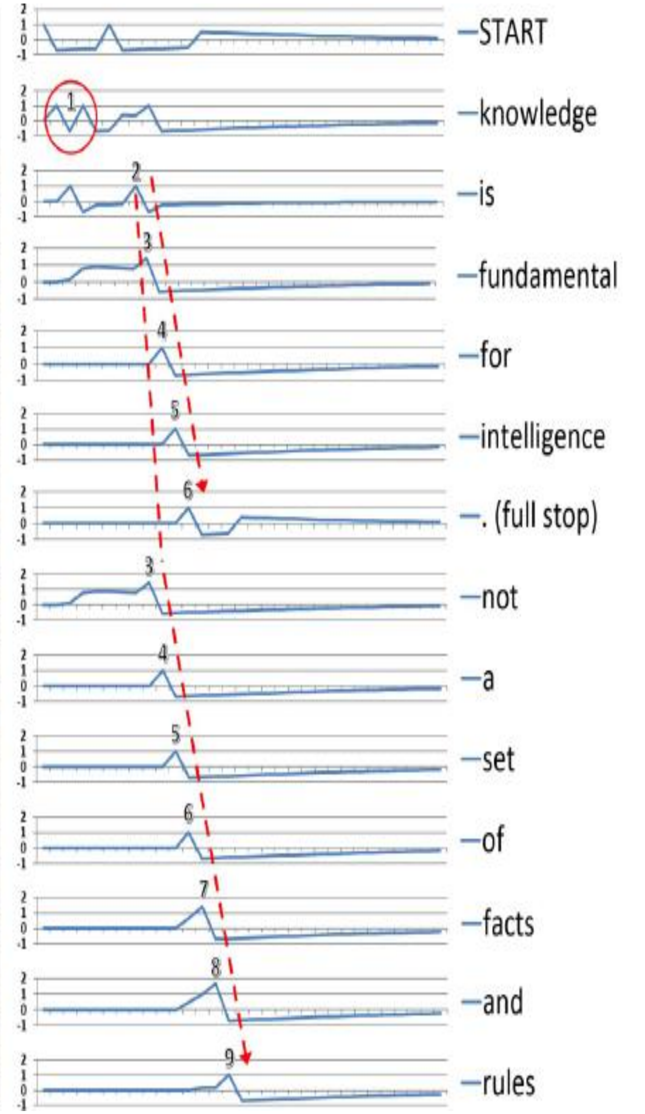
Knowledge is fundamental for intelligence.
Knowledge is not a set of facts and rules.
Knowledge comes into being on the basis of facts and rules.
Knowledge consolidates various facts and rules.
Knowledge aggregates representation of various facts.
Knowledge actively reacts on the represented objects and facts.
Knowledge can be actively represented in the associative systems.

Horzyk, A., *How Does Generalization and Creativity Come into Being in Neural Associative Systems and How Does It Form Human-Like Knowledge?, Neurocomputing, 2014,* ***IF = 1,634****.*


7x START
7x knowledge
1x can
2x is
1x comes
1x be
1x consolidates
1x not
1x into
2x actively
1x fundamental
1x aggregates
1x a
1x being
1x reacts
1x representation
1x set
2x on
2x various
1x for
3x of
3x the
2x represented
1x intelligence
1x basis
1x associative
1x in
1x objects
5x facts
1x systems
4x and
3x rules
7x . (full stop)
ASSOCIATIVE NEURAL STRUCTURE DEVELOPED FOR 7 TRAINING SEQUENCES ABOUT KNOWLEDGE

Reaction on a question: „What is knowledge?”

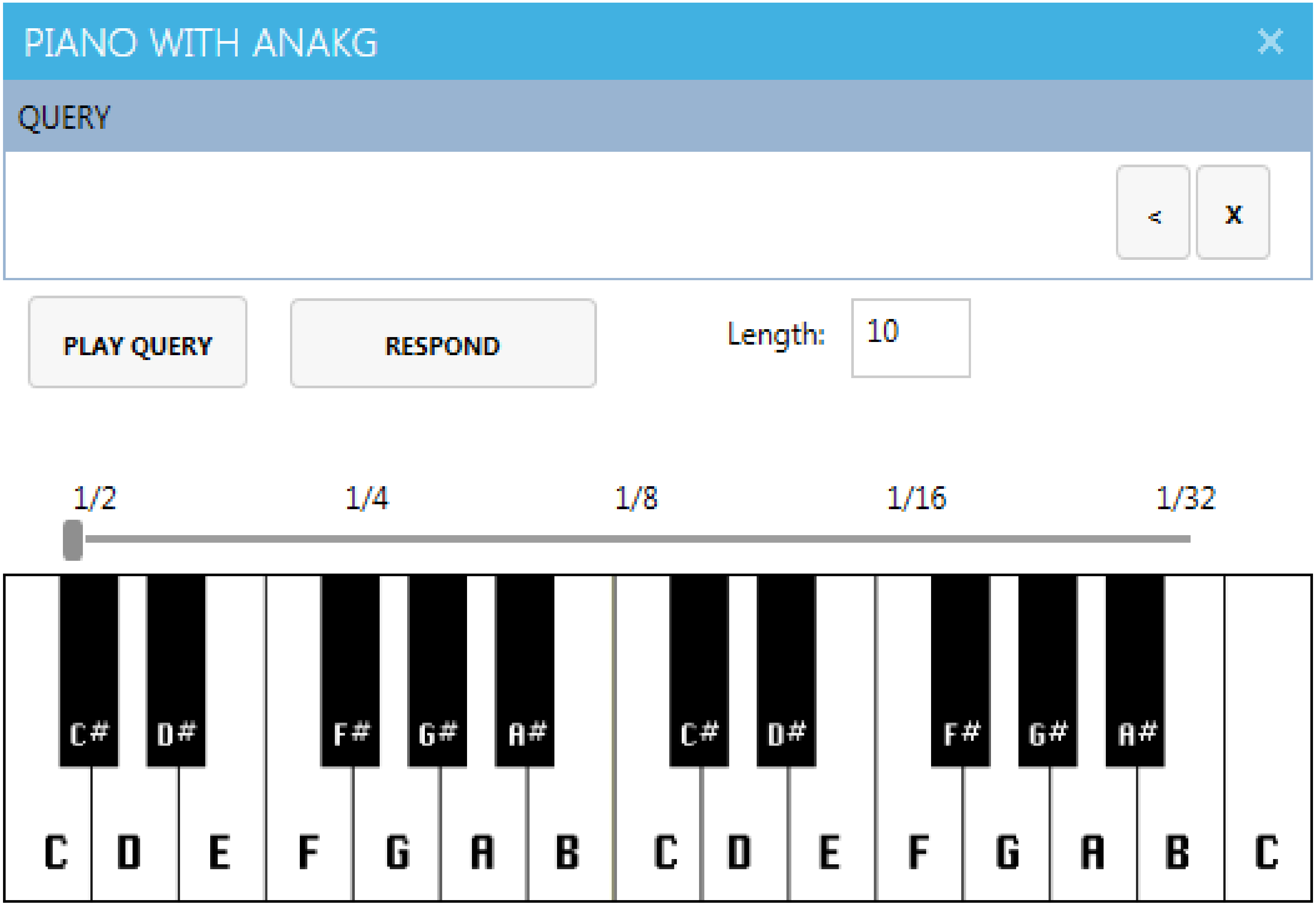
t	START	knowledge	is	fundamental	for	intelligence	not	a	set	of	facts	and	rules	. (full stop)	comes	can	consolidates	actively	reacts	aggregates	OTHERS
0	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
1	-0,70	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
2	-0,66	-0,70	1,00	0,13	0,00	0,00	0,13	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,25	0,25	0,25	0,25	0,13	0,25	0,00
3	-0,63	1,00	-0,70	0,79	0,00	0,00	0,79	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,23	0,23	0,23	0,23	0,12	0,23	0,00
4	-0,59	-0,70	-0,22	0,88	0,00	0,00	0,88	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,46	0,46	0,46	0,46	0,24	0,46	0,00
5	1,00	-0,66	-0,21	0,85	0,00	0,00	0,85	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,43	0,43	0,43	0,43	0,22	0,43	0,00
6	-0,70	0,37	-0,19	0,81	0,00	0,00	0,81	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,40	0,40	0,40	0,40	0,20	0,40	0,00
7	-0,66	0,34	1,00	0,78	0,00	0,00	0,78	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,37	0,37	0,37	0,37	0,18	0,37	0,00
8	-0,63	1,00	-0,70	1,41	0,00	0,00	1,41	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,34	0,34	0,34	0,34	0,17	0,34	0,00
9	-0,59	-0,70	-0,22	-0,57	1,00	0,00	-0,57	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,57	0,57	0,57	0,57	0,28	0,57	0,00
10	-0,56	-0,66	-0,21	-0,54	-0,70	1,00	-0,54	-0,70	1,00	0,00	0,00	0,00	0,00	0,00	0,53	0,53	0,53	0,53	0,26	0,53	0,00
11	-0,52	-0,63	-0,19	-0,50	-0,66	-0,70	-0,50	-0,66	-0,70	1,00	0,67	0,50	0,00	1,00	0,50	0,50	0,50	0,50	0,24	0,50	0,00
12	0,51	-0,59	-0,17	-0,47	-0,63	-0,66	-0,47	-0,63	-0,66	-0,70	1,43	0,97	0,20	-0,70	0,47	0,47	0,47	0,47	0,22	0,47	0,00
13	0,48	-0,56	-0,16	-0,44	-0,59	-0,63	-0,44	-0,59	-0,63	-0,66	-0,70	1,69	0,18	-0,66	0,44	0,44	0,44	0,44	0,20	0,44	0,00
14	0,44	-0,52	-0,14	-0,41	-0,56	-0,59	-0,41	-0,56	-0,59	-0,63	-0,66	-0,70	1,03	-0,63	0,40	0,40	0,40	0,40	0,18	0,40	0,00
15	0,41	-0,49	-0,13	-0,38	-0,52	-0,56	-0,38	-0,52	-0,56	-0,59	-0,63	-0,66	-0,70	0,41	0,38	0,38	0,38	0,38	0,17	0,38	0,00
16	0,38	-0,46	-0,12	-0,35	-0,49	-0,52	-0,35	-0,49	-0,52	-0,56	-0,59	-0,63	-0,66	0,38	0,35	0,35	0,35	0,35	0,15	0,35	0,00
17	0,36	-0,43	-0,11	-0,32	-0,46	-0,49	-0,32	-0,46	-0,49	-0,52	-0,56	-0,59	-0,63	0,35	0,32	0,32	0,32	0,32	0,14	0,32	0,00
18	0,33	-0,40	-0,10	-0,30	-0,43	-0,46	-0,30	-0,43	-0,46	-0,49	-0,52	-0,56	-0,59	0,32	0,30	0,30	0,30	0,30	0,13	0,30	0,00
19	0,30	-0,37	-0,09	-0,28	-0,40	-0,43	-0,28	-0,40	-0,43	-0,46	-0,49	-0,52	-0,56	0,30	0,27	0,27	0,27	0,27	0,11	0,27	0,00
20	0,28	-0,34	-0,08	-0,25	-0,37	-0,40	-0,25	-0,37	-0,40	-0,43	-0,46	-0,49	-0,52	0,27	0,25	0,25	0,25	0,25	0,10	0,25	0,00
21	0,26	-0,32	-0,07	-0,23	-0,34	-0,37	-0,23	-0,34	-0,37	-0,40	-0,43	-0,46	-0,49	0,25	0,23	0,23	0,23	0,23	0,09	0,23	0,00
22	0,24	-0,29	-0,07	-0,21	-0,32	-0,34	-0,21	-0,32	-0,34	-0,37	-0,40	-0,43	-0,46	0,23	0,21	0,21	0,21	0,21	0,09	0,21	0,00
23	0,22	-0,27	-0,06	-0,19	-0,29	-0,32	-0,19	-0,29	-0,32	-0,34	-0,37	-0,40	-0,43	0,21	0,19	0,19	0,19	0,19	0,08	0,19	0,00
24	0,20	-0,25	-0,05	-0,18	-0,27	-0,29	-0,18	-0,27	-0,29	-0,32	-0,34	-0,37	-0,40	0,19	0,18	0,18	0,18	0,18	0,07	0,18	0,00
25	0,18	-0,23	-0,05	-0,16	-0,25	-0,27	-0,16	-0,25	-0,27	-0,29	-0,32	-0,34	-0,37	0,18	0,16	0,16	0,16	0,16	0,06	0,16	0,00
26	0,17	-0,21	-0,04	-0,15	-0,23	-0,25	-0,15	-0,23	-0,25	-0,27	-0,29	-0,32	-0,34	0,16	0,15	0,15	0,15	0,15	0,06	0,15	0,00
27	0,15	-0,19	-0,04	-0,13	-0,21	-0,23	-0,13	-0,21	-0,23	-0,25	-0,27	-0,29	-0,32	0,15	0,13	0,13	0,13	0,13	0,05	0,13	0,00
28	0,14	-0,17	-0,04	-0,12	-0,19	-0,21	-0,12	-0,19	-0,21	-0,23	-0,25	-0,27	-0,29	0,13	0,12	0,12	0,12	0,12	0,05	0,12	0,00
29	0,12	-0,16	-0,03	-0,11	-0,17	-0,19	-0,11	-0,17	-0,19	-0,21	-0,23	-0,25	-0,27	0,12	0,11	0,11	0,11	0,11	0,04	0,11	0,00
30	0,11	-0,14	-0,03	-0,10	-0,16	-0,17	-0,10	-0,16	-0,17	-0,19	-0,21	-0,23	-0,25	0,11	0,10	0,10	0,10	0,10	0,04	0,10	0,00



As-neurons are activated in a specific order that returns the following answers:

- *Knowledge is fundamental for intelligence.*
- *Knowledge is not a set of facts and rules*

GENERALIZATION OF PIANO SONGS

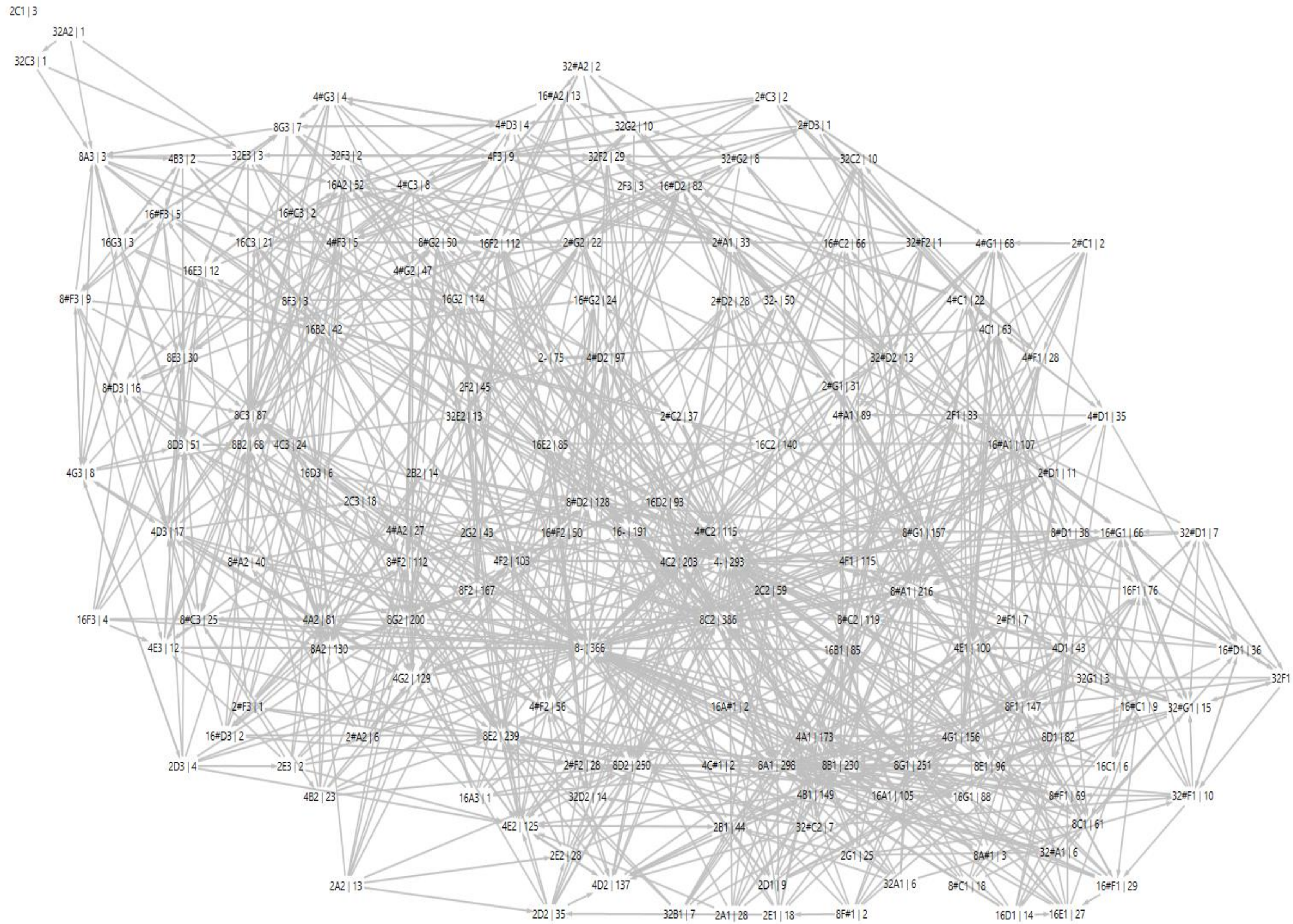


ASSOCIATIVE NEURAL GRAPH FOR PIANO SONGS

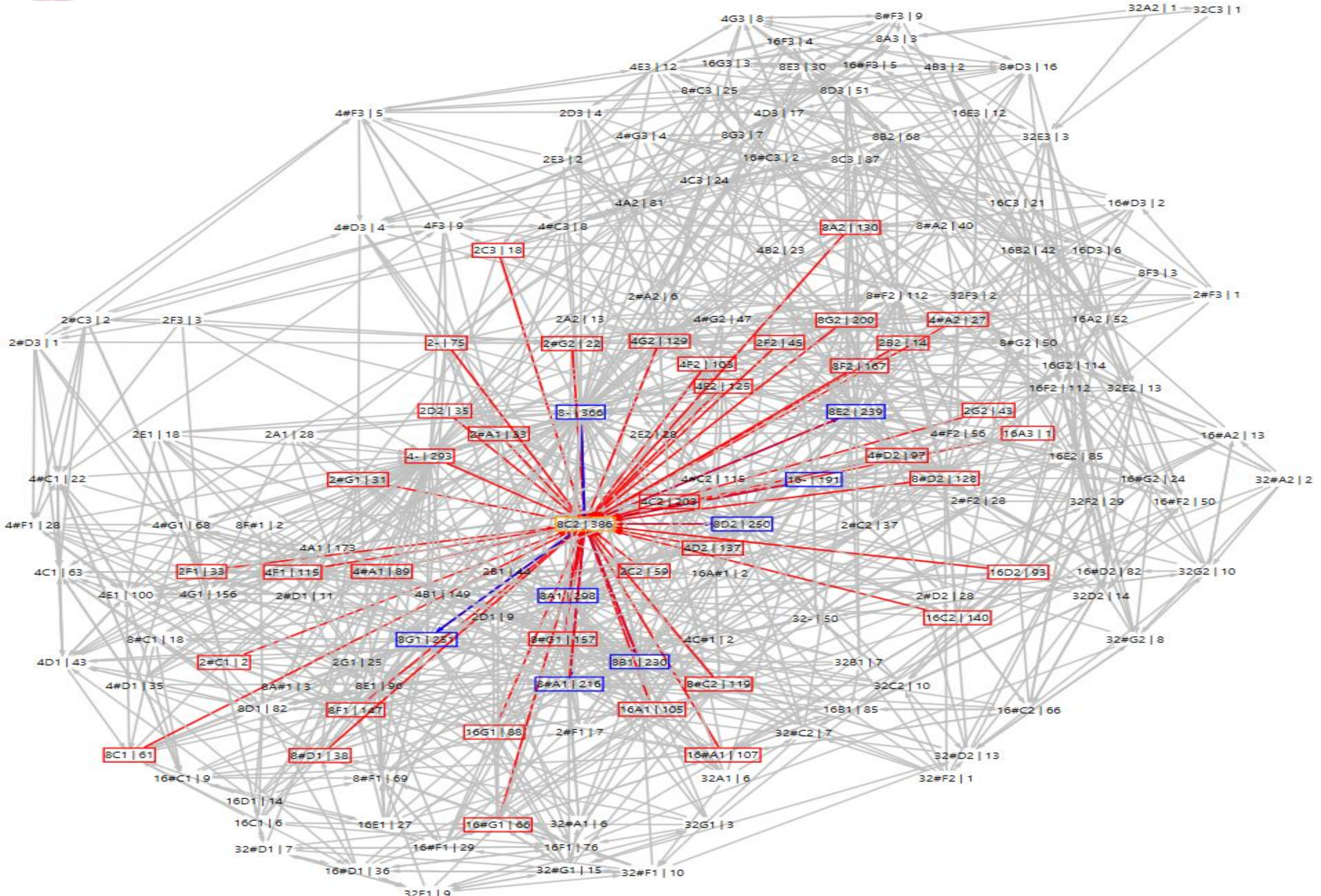
0.70x

1:1

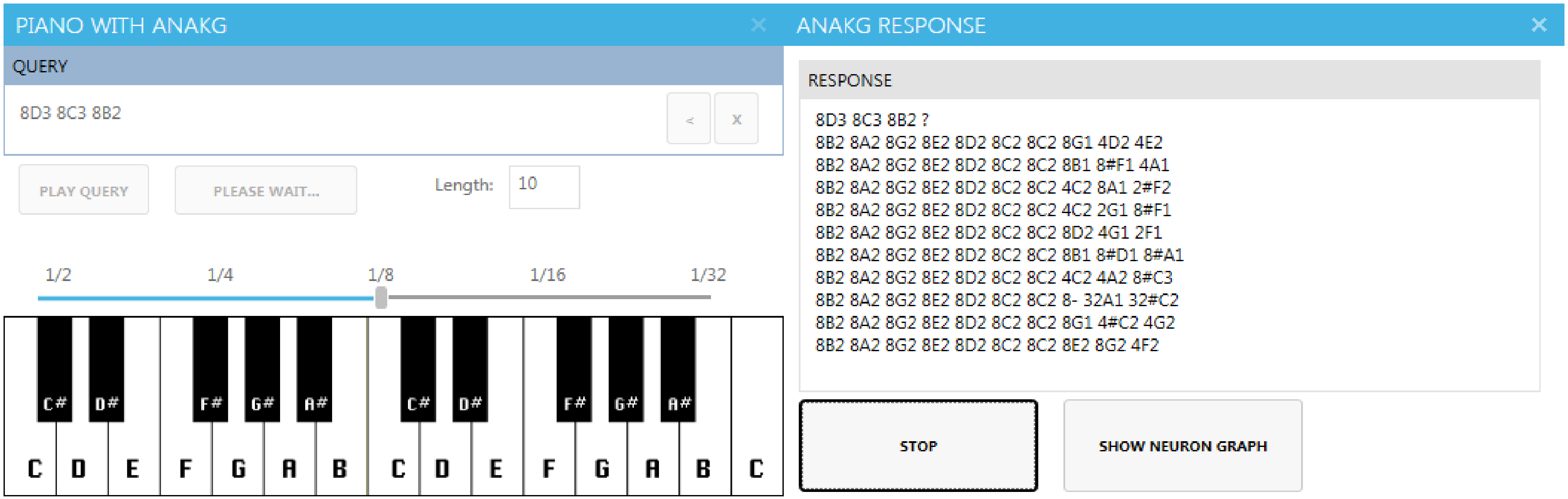
Fill

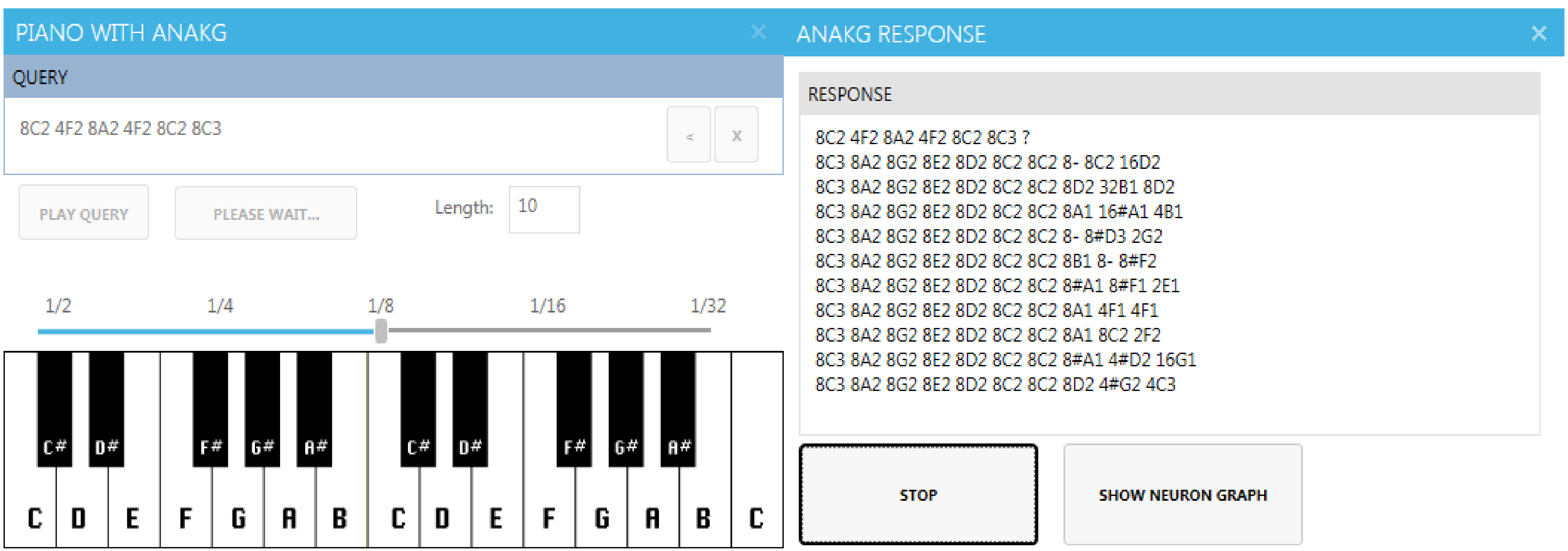


ASSOCIATIVE NEURAL GRAPH FOR PIANO SONGS



GENERALIZATION OF PIANO SONGS





WHAT IS REALLY IMPORTANT IN ANAKG?

ACTIVE ASSOCIATION is more then a simple connection between represented elements. It connects them actively.

Active connections can be automatically triggered off.

Active associations make possible to automatically recall other associated objects.

We can associate whatever, not only similar objects.

Sequencial objects are automatically associated by brains.

Associating of following objects allows us to learn whatever.

Similar objects are usually represented by the same neurons that in real terms represent classes of similar objects.

Active associations enable us not to search or loop for data!

FINAL CONCLUSIONS AND REMARKS

1. **New model of neurons: AS-NEURONS.**
2. **New associative mechanisms that are able to operate on graphs of neurons.**
3. **New method for adapting parameters of associative neural graphs ANAKG-2**
4. **New approach to conduct computations using as-neurons and presented graphs**
5. **New generalization ability of these graphs on a sequence level.**

BIBLIOGRAPHY

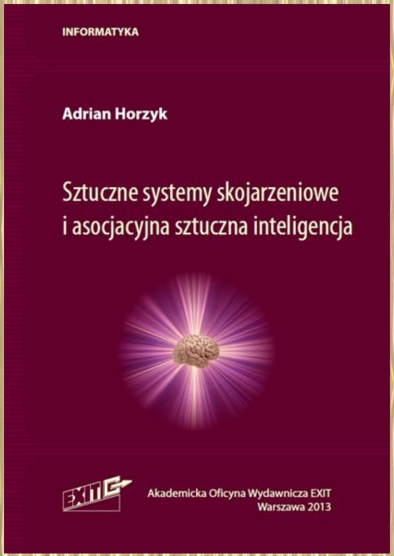
1. **Horzyk, A.**, *Innovative Types and Abilities of Neural Networks Based on Associative Mechanisms and a New Associative Model of Neurons,* the invited talk at the ICAISC 2015, Springer Verlag, LNAI 9119, 2015, pp. 26-38.
2. **Horzyk, A.**, *How Does Generalization and Creativity Come into Being in Neural Associative Systems and How Does It Form Human-Like Knowledge?*, **Neurocomputing**, 2014, **IF = 1,634**.
3. **Horzyk, A.**, *Human-Like Knowledge Engineering, Generalization and Creativity in Artificial Neural Associative Systems*, Springer, AISC 11156, 2014.
4. **Horzyk, A.**, Human-Like Knowledge Engineering, Generalization and Creativity in Artificial Neural Associative Systems, Springer Verlag, AISC 11156, ISSN 2194-5357, 2015.
5. **Horzyk, A.**, Innovative Types and Abilities of Neural Networks Based on Associative Mechanisms and a New Associative Model of Neurons - referat na zaproszenie na międzynarodowej konferencji ICAISC 2015, Springer Verlag, LNAI, 2015.
6. **Horzyk, A.**, *Sztuczne systemy skojarzeniowe i asocjacyjna sztuczna inteligencja*, EXIT, Warszawa, 2013.
7. Tadeusiewicz, R., **Horzyk, A.**, *Man-Machine Interaction Improvement by Means of Automatic Human Personality Identification*, Gerhard Goos, Juris Hartmanis, and Jan van Leeuwen (Eds.), Springer, LNCS 8104, 2013.
8. **Horzyk, A.**, Gadamer, M., *Associative Text Representation and Correction*, Springer Verlag Berlin Heidelberg, LNAI 7894, 2013, pp. 76-87.
9. **Horzyk, A.**, *Information Freedom and Associative Artificial Intelligence*, Springer Verlag Berlin Heidelberg, LNAI 7267, 2012, pp. 81-89.
10. **Horzyk, A.**, *Self-Optimizing Neural Network 3*, L. Franco, D. Elizondo, J.M. Jerez (eds.), Constructive Neural Networks, Springer, Series: Studies in Computational Intelligence, Vol. 258, 2009, pp. 83-101.
11. Dudek-Dyduch, E., Tadeusiewicz, R., **Horzyk, A.**, *Neural Network Adaptation Process Effectiveness Dependent of Constant Training Data Availability*, **Neurocomputing** 72, 2009, pp. 3138-3149, **IF = 1,440**.

Google: Horzyk OR http://home.agh.edu.pl/~horzyk/index-eng.php

Google: Horzyk

horzyk@agh.edu.pl

AGH



Innovative Types and Abilities of Neural Networks Based on Associative Mechanisms and a New Associative Model of Neurons

Adrian Horzyk

horzyk@agh.edu.pl

Google: Horzyk

AGH University of Science and Technology

Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering

Department of Automatics and Biomedical Engineering

Poland, 30-059 Krakow, Mickiewicza Av. 30, C3/205

http://home.agh.edu.pl/~horzyk/index-eng.php