Chapter 11
Flexibility and Adaptivity of Emotion Regulation: From Contextual Dynamics to Adaptation and Control

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Abstract To effectively regulate their emotions, people have to continually adjust their emotion regulation strategies to changes in internal and external demands. Flexibility and adaptivity are thus vital to emotion regulation. Flexibility refers to the context-sensitive deployment of emotion regulation strategies while regulating one's own emotions. By contrast, adaptivity refers to the changes in such context-sensitive deployment of strategies that take place while regulating one's own emotions over time, and the control of such change processes. Flexibility is increased by having larger repertoire of strategies as this increases the odds that an appropriate strategy is available. On the other hand, having more emotion regulation strategies to choose from creates the need for decision. Because this decision-making process occurs in real time, it requires emotional stability and cognitive analysis. Over time, different experiences in choosing emotion regulation strategies give rise to learning which is one form of adaptivity. Flexibility in emotion regulation is provoked by the fluctuating contexts, whereas adaptations are induced by the frequency and intensity of emotion-regulatory activities. These adaptations are grounded in changes at a cellular and molecular level. The latter adaptations are often referred to by the term plasticity, or first-order adaptation. Often some form of control is applied to such adaptation processes, determining when and under which circumstances the adaptations should take place; this is often referred to by the term meta-plasticity or second-order adaptation. The above concepts are illustrated by simulated example scenarios based on different computational network models. In the first simulated scenario, a varying context shows the flexibility in the choice of emotion regulation strategies. In the second and third scenario, plasticity and meta-plasticity are illustrated based on first- and second-order adaptive network models.

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C. E. Waugh, P. Kuppens (eds.), *Affect Dynamics*,
https://doi.org/10.1007/978-3-030-82965-0_11

11.1 Introduction

People use a wide variety of strategies in regulating their emotions (Koole, 2009; Gross, 1998; Parkinson & Totterdell, 1999). The efficacy of these emotion-regulation strategies employed by a person depends on the (person-specific and external) circumstances in which the strategies are employed. As such, the question arises how people are able to flexibly adapt their use of emotion regulation strategies to shifting situational demands; see also (Aldao et al., 2015). Consider, for instance, the following scenario: You are an office worker who feels hurt every time his colleagues criticize him. To regulate your emotions, you have various options: Walking away, distracting yourself, hiding your reaction, or mentally distancing yourself from your colleagues. Which of these options is optimal depends on the situation. For instance, if the critical colleague is your manager, then walking away is probably not advisable. Alternatively, if the critical colleague is your best friend, then mental distancing may hurt your friendship. Each emotion regulation strategy employed by a person can thus have different results and implications in different (person-specific and external) situations (Aldao, 2013). This is why it is fortunate that people have the capability to flexibility choose between various emotion regulation strategies as per demands of the (both person-specific and external) situation. This capacity is referred to as emotion regulation flexibility (Aldao et al., 2015; Bonanno & Burton, 2013a).

Aside from the flexibility in choice of emotion regulation strategies as per demand of the context, another type of change in the choice of emotion regulation strategies has now been quite extensively discussed in the cognitive, neuro and social sciences (Carstensen et al., 1999). Emotion regulation is a specific form of mental process, like any mental process grounded in the underlying neural mechanisms. In a wider context, according to the neurocognitive science literature, *synaptic* plasticity forms the biological basis for many forms of adaptation (Hebb, 1949); this actually is a form of first-order adaptation. Furthermore, many studies have reported systematic changes in synaptic plasticity that imply a form of control over the plasticity; this has been called *metaplasticity (*Abraham*,* 2008*;* Abraham & Bear*,* 1996*)* and represents a form of second-order adaptation.

Plasticity and metaplasticity in addition to the base dynamics lead to rather complex and usually circular processes, which makes it a challenge to model them computationally. To address such a challenge, recently in the field of Network Science and Artificial Intelligence a suitable Network-Oriented Modeling method based on self-modeling networks has been introduced (Treur, 2019, 2020a). Using this modeling approach a base network is can be extended into a multi-level adaptive network model by adding self-models to it for some of its network characteristics. A first-order self-model can be used to represents first-order adaptation or plasticity and a second-order self-model to represent second-order adaptation or metaplasticity. This has been applied in particular to emotion regulation in (Ullah et al., 2020a). These levels or orders of adaptation can still go higher if the phenomenon itself needs it, for instance (Ullah & Treur, 2020a) presents a fourth-order adaptive network model.

In the remainder of this chapter, we develop computational models of flexibility and adaptivity in emotion regulation. In Sect. 11.2, we start by analyzing the dynamics for contextual flexibility in emotion regulation, In Sect. 11.3, we take a closer look at first-order adaptation in emotion regulation, In Sect. 11.4, we turn to higher-order adaptation and metaplasticity in emotion regulation. Finally, we summarize our main conclusion in Sect. 11.5, and provide references and appendices respectively.

11.2 Dynamics for Contextual Flexibility in Emotion Regulation

11.2.1 Contextual Flexibility in Emotion Regulation

Emotion regulation theorists have distinguished between five families (or broad categories) of emotion regulation strategy (Gross, 1998, 2015; Richards & Gross, 2000). The first family of emotion regulation strategies is to change the kind of situation one is in. For instance, the office worker from Sect. 11.1 can choose to walk outside the office. The second family of emotion regulation strategies focuses on modifying aspects of the situation. For instance, our office worker could hang a 'do not disturb' sign by his door to keep the critical colleague at bay. The third family of emotion regulation strategies focuses on changing where one attends. For instance, our office worker could distract himself by mentally planning dinner. The fourth family of emotion regulation strategies consists of changing the interpretation of the situation. For instance, our office worker could tell himself that the critical colleague really means well. Finally, the fifth family of emotion regulation strategies consists of modulating one's outward emotional responses. For instance, our office worker could actively try to smile to the critical colleague, even while stewing with anger inside.

Initially, emotion regulation researchers assumed that some families of emotion regulation strategies are generally more effective than others. For instance, cognitive change strategies were believed to be more effective than response modulation strategies (Gross, 2001). However, subsequent research revealed that general differences in effectiveness between emotion regulation strategies are small (Aldao & Nolen-Hoeksema, 2012). Moreover, even cognitive change strategies like reappraisal, that are generally effective, may have disadvantages in certain situations (Ford & Troy, 2019). Conversely, there are situations where the use of a response modulation strategy like expressive suppression can prove quite adaptive (Dworkin et al., 2019). Effective emotion regulation thus appears to be not so much a matter of using some strategies and avoiding others. Instead, effective emotion regulation is a matter of finding the right strategy for the situation. This means that flexibly adapting emotion regulation to situational demands plays a vital role in emotion regulation (Aldao, 2013; Gross, 2015; Bonanno & Burton, 2013b; Sheppes, 2014; Webb et al., 2012a).

Empirical research on emotion regulation flexibility has so far been limited. This is one of the reasons why previous work (Sheppes et al., 2011) and our own previous computational model of emotion regulation flexibility (Ullah et al., 2018) that was mainly based on that, only focused on the choice between attention deployment and reappraisal. Going beyond this work, however, this section of the chapter illustrates flexibility by a simulated scenario that involves flexibility among four emotion regulation strategies as per demand of the context.

11.2.2 *Simulated Scenarios for Contextual Flexibility in Emotion Regulation*

The simulated scenarios presented in this section illustrate the ability to respond to four different situations with different regulation strategies. First, in Sect. 11.2.2.1 the computational network used is briefly explained, next, in Sect. 11.2.2.2 the four simulated scenarios are shown.

11.2.2.1 The Computational Network Model for Contextual Flexibility

Figure 11.1 presents the connectivity of the network model used, with its nomenclature in Table 11.1.

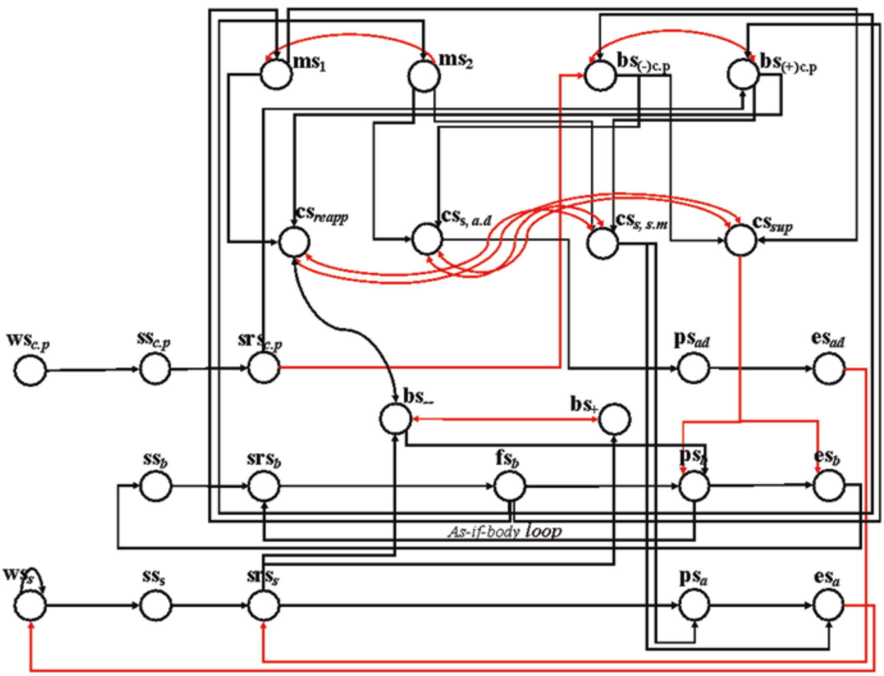

Fig. 11.1 Connectivity of the computational network model used for flexibility; here the red connections are suppressing connections: they have a negative weight (see also Table 11.7 in Appendix 1)

Table 11.1 Nomenclature of the states of the network model used

States	Informal name	Description
ws_s	World state for stimulus *s*	The situation in the real world that triggers emotion
$ws_{c.p}$	World state for context pressure	A real-world situation which decides expression of emotion
ss_s	Sensor state for stimulus *s*	Sensor state for the stimulus *s* in the real world
$ss_{c.p}$	Sensor state for context pressure	Senses state for context pressure
ss_b	Sensor state for body	Sensor state for body state *b* relating to a negative emotion
srs_s	Sensory representation state for stimulus *s*	Internal representation of the emotion triggering situation
$srs_{c.p}$	Sensory rep: state for context pressure	Internal representation of the context pressure in the real world
srs_b	Sensory representation state for body	Internal body representation state for *b* relating to a negative emotion
bs_-	Negative believe state	The negative believe that the person has about something/someone
bs_+	Positive believe state	The positive believe that the person has about something/someone
ms_1	Monitoring state for low emotion level	Monitors for low emotions
ms_2	Monitoring state for high emotion level	Monitors for high emotions
$bs_{(+)c.p}$	Belief state for context pressure	Believing that expression of emotion will matter in the environment
$bs_{(-)c.p}$	Belief state for context pressure	Believing that expression of emotion won't matter in the environment
cs_{reapp}	Control state for reappraisal	Controlling negative beliefs about something/someone
$cs_{s,a.d}$	Control state for attention deployment	Control state for Attention Deployment
$cs_{s,s.m}$	Control state for situation modification	Control state for situation modification as a result of context
cs_{sup}	Control state for suppression	Control state for Suppression of Expression
fs_b	Feeling state for body state *b*	Feeling associated to body state *b*; this is a negative feeling
ps_a	Preparation state for action a	Preparing for action *a*
ps_b	Preparation for body state *b*	Preparation state for body state *b* relating to a negative emotion
ps_{ad}	Preparation state for attention deployment	Preparation for the Attention deployment action
es_a	Execution state for action *a*	Execution station for action *a*
es_b	Execution state for body state *b*	Execution state for body state *b*, bodily expressing a negative emotion
es_{ad}	Execution state for attention deployment	Execution state for the Attentional Deployment action

Table 11.2 Choice of strategies under high/low intensity of emotions and +/− belief about context pressure

Flexibility parameters		Repertoire of strategies			
Emotion strength	Context pressure (CP)	Situation modification	Attention deployment	Cognitive reappraisal	Expressive suppression
+	+	✓			
+	−		✓		
−	+			✓	
−	−				✓

The computational network model used here inherits flexibility in emotion regulation strategies from (Ullah et al., 2018) and decision-making from (Manzoor et al., 2017). In this model, the phenomenon of emotional arousal and its regulation has been modeled. The emotion eliciting stimulus is taking place as the world state ws_s which activates sensor state ss_s and sensor representation state srs_s. Based on the internal valuation and prior beliefs about the stimulus, the person's feelings gets activated and keeps increasing as a result of internal as-if-body-loop as explained by Damasio (Bechara et al., 2003). On the basis of the intensity of emotions monitored by the monitoring state ms_1 and ms_2, i.e., low and high intensity of emotions, respectively, are activated which then activates the respective control state cs for strategy (cs_{reapp}, $cs_{s.\ a.\ d}$, $cs_{s.\ s.\ m}$, and cs_{sup}) as represented in Table 11.2 below. Empirically, these models can be verified against the literature as described above, representing how specific areas in the brain are casually activated and involved in the generation and regulation of emotions. For instance, the amygdala and prefrontal cortex are the main brain regions involved in this process of emotion generation, valuation of stimulus and regulation of emotions. However, without extensively going into all technical details of the model, the connectivity picture in Fig. 11.1 can be understood as a causal diagram where it is indicated which state is causally affected by which other states. The considered model presented in Fig. 11.1, has the capability to switch between four different strategies (with control states cs_{reapp}, $cs_{s.\ a.\ d}$, $cs_{s.\ s.\ m}$, and cs_{sup}), depending on the situational aspect combinations as shown in Table 11.2. An extensive overview of the modeling approach from (Treur, 2020a, 2016), used for the network model can be found in Appendix 1.

The first column, in Table 11.2, represents the intensity of the emotions: high (+) or low (−). The second column represents the belief about the context pressure during the emotion eliciting situation. This is a kind of prediction for the environment where the (+) means presence of a context factor due to which the expression of emotions can have negative consequences and (−) refers to a context where expression of emotions doesn't matter.

11.2.2.2 Four Simulated Example Scenarios Addressed for Contextual Flexibility

For the four simulated scenarios, the following basic setup is considered

> "An employee A feels angry every time a particular obnoxious coworker B starts talking. Next week the organization has a monthly meeting where presence of all employees is mandatory unless emergency, and where the boss may or may not show up. Employee A doesn't want anyone, especially his boss to come to know about his attitude towards employee B. Employee A has four options to handle the situation, all depending upon the combination of his intensity of emotions and the chances of presences or absence of their boss at the working place as shown in Table 11.2."

All values for the network characteristics used for the model are given in Table 11.6 and 11.7 in Appendix 2; they qualitatively validate the model used against the findings from empirically founded literature that serve as qualitative evaluation indicators. These values are essential for the reproduction of the model; they provide the simulation results as shown in Figs. 11.2, 11.3, 11.4, and 11.5. All simulation graphs only display the most essential states for the explanation of the scenario.

Figure 11.2 depicts a scenario for low (−) intensity of emotions and positive (+) belief about CP; this combination triggers the negative belief state bs_- and (potentially) in turn the negative emotional response preparation ps_b and by the as-if body loop also the negative feeling state fs_b and due to that the control state for reappraisal cs_{reapp}. The figure also demonstrates the way reappraisal works. As reappraisal alters the interpretation of the stimuli, this can be seen in the figure where initially the negative belief bs_- gets quite high but it starts decreasing as soon as the control state for reappraisal cs_{reapp} gets activated. This control state cs_{reapp} takes care of altering the interpretation of the stimuli: by suppressing the negative belief bs_-, in turn the positive belief bs_+ increases which (cyclically) again additionally

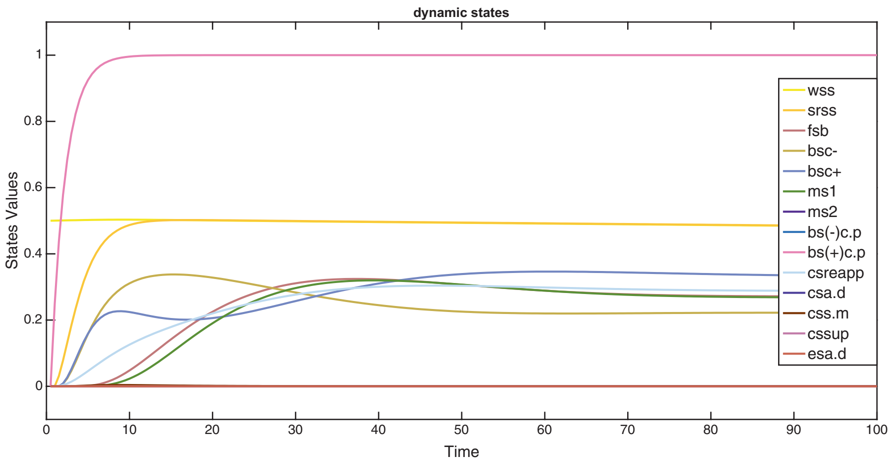

Fig. 11.2 Reappraisal: low intensity negative emotions with context pressure

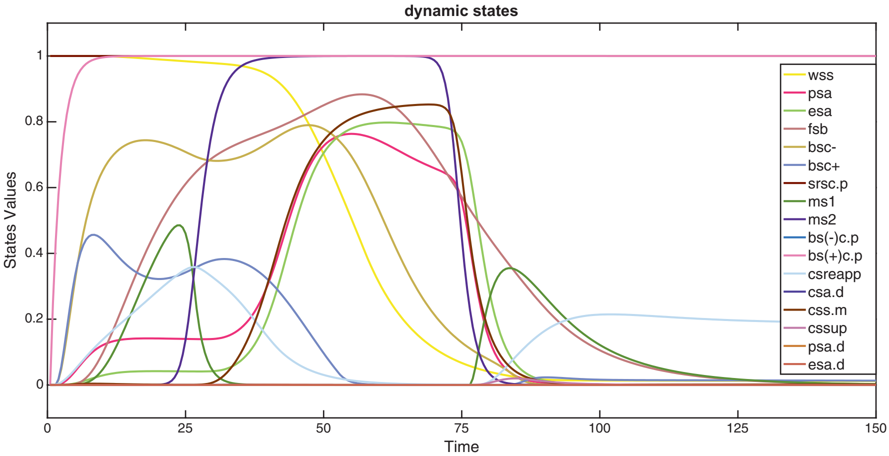

Fig. 11.3 Situation modification: high intensity negative emotions with context pressure

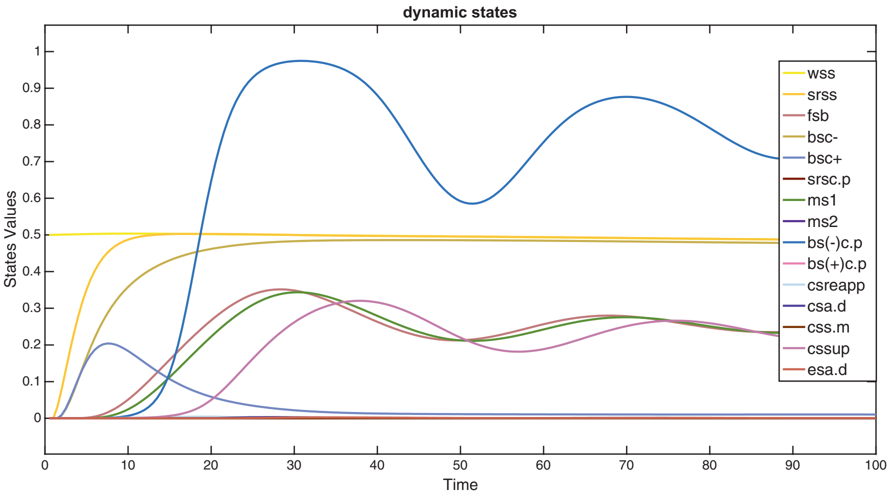

Fig. 11.4 Expressive suppression: low intensity negative emotions with no context pressure

suppresses the negative belief bs_{-}, as a result of which the preparation for the negative emotional response ps_b and in turn (by the as-if body loop) the negative feeling state fs_b also decrease.

In Fig. 11.3, a context with high (+) intensity of emotions and positive (+) belief about CP is shown which activates situation modification $cs_{s.m}$ as an emotion regulation strategy. Here the context pressure motivates the person to hide his emotions. In case of a development of a high intensity of negative emotions, the emotion level starts from 0 after which it gradually goes to low and to high. Therefore, in Fig. 11.3 initially the regulation starts for a combination with low emotion as demonstrated in Fig. 11.2. Later on, as the negative emotions get higher than the low emotions range, the control state for situation modification $cs_{s.\ m}$ gets activated. Situation

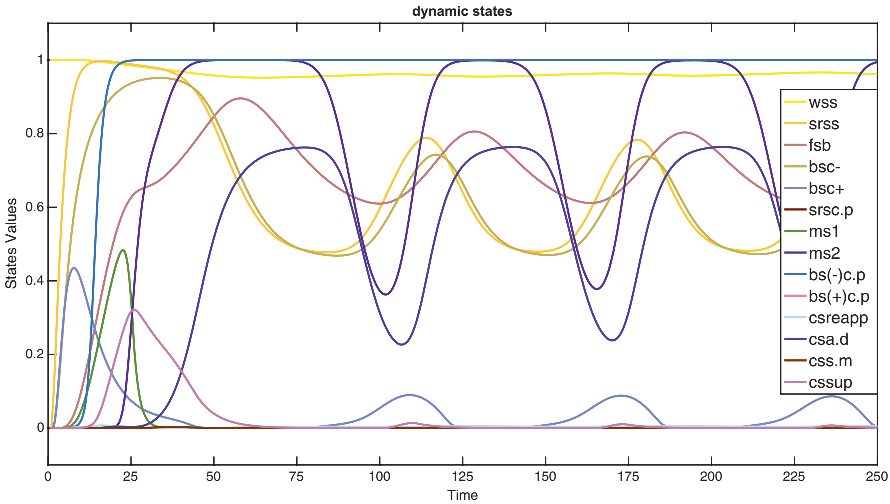

Fig. 11.5 Attention deployment: high intensity negative emotions with no context pressure

modification as a strategy means modifying/leaving the emotional situation, i.e., the world state ws_s for the stimulus. Therefore, it can be observed in the figure that the world state ws_s starts decreasing as soon as the preparation ps_a for the appropriate physical action a (e.g., changing position or walking away) and execution es_a of this physical action takes place. This means the person has somehow left the emotional situation and, therefore, his negative emotions also decrease. While emotions of the person are decreasing, this gets into the low emotional zone once again. Therefore, in the figure it can be seen that in that situation reappraisal gets activated accordingly, like in the scenario of Fig. 11.2.

As highlighted in Table 11.2, the combination of low (−) intensity of emotion and negative (−) belief about CP which means no context pressure, activates expressive suppression cs_{sup}. In Fig. 11.4 it can be observed that initially negative feeling state fs_b increases as the negative belief bs_- increases. The increase stops as soon as the control state for suppression cs_{sup} gets activated which suppresses the negative emotional response preparation ps_b and execution es_b which in turn (by the as-if body loop) induces less negative feelings.

As suppression only suppresses the preparation and expression of the emotions and does not affect the causes of the emotional response, the sensor representation state srs_s and negative belief state bs_- for the negative interpretation still remain high, which by many is considered an unhealthy and stressful internal state.

Figure 11.5 represents a context with high (+) intensity of emotions and negative (−) belief about CP, which means that the person can afford it if his emotions are seen by others. This activates attention deployment $cs_{a.d}$ as a main strategy for emotion regulation. This context also has two strategies to deal with just as described in Fig. 11.3. Initially, when the emotions are yet to get high, the person tries to suppress his emoting by using expressive suppression cs_{sup}. Later on, as the emotions get high enough, the person tries to downregulate his emotions by using attention deployment $cs_{a.d}$ where he distracts his attention.

11.3 Plasticity in Emotion Regulation

11.3.1 Adapting how to regulate emotions over time

By flexibly regulating their emotions, people adapt their emotion regulation to different situations. Given that recurring situations are likely to give rise to similar emotion regulation strategies, the person is likely to display certain predictable patterns in emotion regulation patterns. These patterns, in turn, may give rise to long-term adaptations in emotion regulation. These long-term adaptations are captured by the notion of synaptic plasticity.

Synaptic plasticity provides a main neurochemical foundation to learning and memory formation. It refers to the ability of the connections between neurons to get stronger or weaker over time. A synapse refers to the structure that enables an electrical or chemical signal to pass from one neuron to another neuron or a target effector cell. This increase or decrease in the strength of synapse depends upon the neurons' current or recent activation. This has been formulated by Donald Hebb (Hebb, 1949), p. 62, as:

> 'When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased'.

This process, which has become widely known as Hebbian learning. But note that in the above quote Hebb does not call it learning; it only describes changes in 'one or both cells' over time. Sometimes it is summarized in a simplified form as 'neurons that fire together, wire together'. Hebbian learning entails that simultaneous activation of the neurons/cells strengthens the synapses between those two neurons/cells. This is a biological basis for learning. In terms of emotions and specifically emotion regulation, (Giuliani et al., 2011) has studied excessive employment of expressive suppression and brain structures such as in the anterior insula and has come up with positive relation between them. It has been found, for example, that the volume of anterior insula increases as a result of more use of expressive suppression for emotion regulation. Similarly, (Ostroumov & Dani, 2018) provides an extensive review on neuronal plasticity and metaplasticity as a result of stress, nicotine and alcohol. Moreover, reward-driven and prediction-driven synaptic plasticity and hence learning has been explained in (Schultz et al., 1997). In terms of computational modeling, various examples of adaptive computational models can also be found, for instance in (Ullah & Treur, 2019) reward based learning has been demonstrated based on a Hebbian learning process. Similarly, (Zegerius & Treur, 2020) models the working of Eye Movement Desensitization and Reprocessing (EMDR) therapy for persons affected by a Post-Traumatic Stress Disorder (PTSD) by a therapy-induced Hebbian learning process.

Particularly relevant to plasticity of emotion regulation are (Zimmermann & Iwanski, 2014) differences in emotion regulation strategies between young and older adults. The 'Strength and vulnerability integration theory' (Charles, 2010) provides a reason for this shift by stating that it becomes more difficult for an older person to apply response-focused strategies due to less physiological flexibility for higher age. Some other studies agree to these finding and come up with strategies focused findings, for instance, (John & Gross, 2004; Charles & Carstensen, 2007) associate more use of reappraisal at an older age. Moreover, studies like (Lawton et al., 1992; Phillips et al., 2006), also consider older people to be better in controlling emotional situations and quicker in regaining positive mood as compared to the younger adults (Carstensen et al., 2000; Larcom & Isaacowitz, 2009). Furthermore, (Yeung et al., 2011) attributes this retention of positive mood in older people to reappraisal being used as an adaptive emotion regulation strategy. In contrast to suppression, some studies also consider reappraisal more helpful in decreasing psychological distress (Haga et al., 2009; John & Gross, 2004). In case of expressive suppression, even successful suppression doesn't ensure decrease in distress (Gross et al., 1997) but younger adults still would use suppression, maybe because they prefer confrontational coping (Folkman et al., 1987). Similarly, there are various studies which support the notion of increased use of reappraisal by older people and more use of suppression by younger people subject to various possible reasons like the availability of physiological resources, motivational goals, priority given to the emotional wellbeing (Nakagawa et al., 2017; Scheibe & Blanchard-Fields, 2009; Scheibe & Carstensen, 2010; Cutuli, 2014).

Although individual differences do matter for all these changes (Rothbart et al., 2000), there appear to be developmental changes in regulatory capabilities in the later half of adult life. In line with these concepts, according to plasticity (Labouvie-Vief et al., 1989), improvement in cognitive reappraisal as a strategy is essential for maturity in cognition and, therefore, as compared to younger people, older people display more cognitive maturity (Labouvie-Vief & Blanchard-Fields, 1982). Similarly, goal adjustment flexibility is stronger in older persons (Heckhausen & Schulz, 1995; Brandtstädter & Renner, 1990).

Note that all these phenomena that seem to have correlations to age, do not have any causal relation to a notion of age, as age by itself does not cause anything. Such correlations are an emerging result of adaptive processes based on underlying mechanisms where the actual causal relations and pathways can be found. These mechanisms will be discussed in some detail in the current and next section.

11.3.2 Simulated Scenarios for Plasticity in Emotion Regulation

The simulated scenarios presented in this section illustrate the ability to adapt the choice of emotion regulation strategies over time. The differences in emotion regulation strategies for different ages as discussed above will be used for this. First, in Sect. 11.3.2.1 the first-order adaptive computational network used is briefly explained, next, in Sect. 11.3.2.2 a simulated scenario is shown.

11.3.2.1 A First-Order Adaptive Network Model for Plasticity in Emotion Regulation

This section introduces the first-order adaptive network model used for the simulated scenario. The connectivity of the adaptive network model is shown in Fig. 11.6 with an overview of its states in Table 11.3. This first-order adaptive network model, models plasticity of the choice of emotion regulation strategies. Here, the base network models the basic functioning of two well-known emotion regulation strategies: cognitive reappraisal and expressive suppression.

In the base model, as in the model in the previous section, the world state ws_s represent the stimulus in the world that triggers some kind of emotions after the basic processing of the stimulus, i.e., through sensor ss_s, sensor representation state srs_s, and valuation of the stimulus that is the belief of the person about the stimulus. On the basis of beliefs, i.e., bs_- or bs_+ about the stimulus the internal as-if-body-loop of the person gets activated which slowly and gradually increases the feelings of the person that can be positive as well as negative, but here the focus is on negative feelings represented by fs_b. The control state for reappraisal cs_{reapp} represents cognitive reappraisal which regulates emotions by changing one's belief or interpretation for the stimulus. Control state cs_{sup} represents expressive suppression which suppression expression of emotions.

State ms_{dstrss} represents the monitoring state for distress, which according to the literature should remain high if a person is suppressing his/her emotions and should remain low if a person is reappraising his/her emotions.

The self-model modeled in the upper (blue) plane addressing the first-order adaptation, represents the Hebbian learning principle described in Sect. 11.3.1. This adaptation process takes place over the entire life span of an individual. The person uses suppression during the first phase of his life and then switches to reappraisal in the later phase of his life, based on his activations of strategies. This is an emergent effect of the mechanism of Hebbian learning: simultaneous activations of the

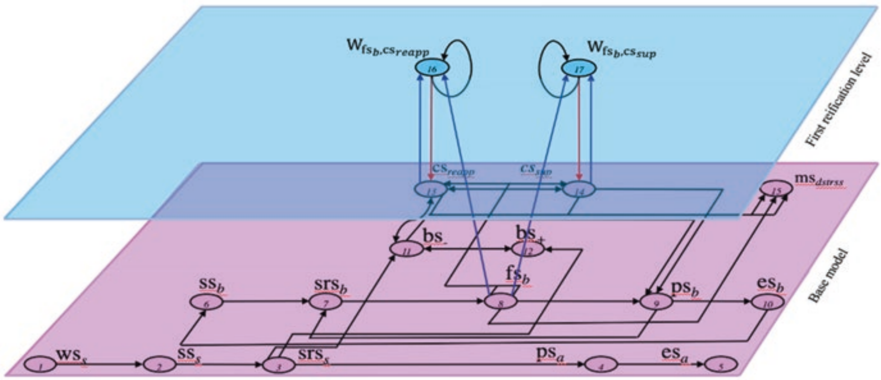

Fig. 11.6 First-order adaptive network model for emotion regulation strategy choice adapting over a longer time

Table 11.3 Overview of the states of the first-order adaptive network model

State		Explanation	Level
X_1	ws_s	World state for stimulus s	Base states
X_2	ss_s	Sensor state for stimulus s	
X_3	srs_s	Sensory representation state for stimulus s	
X_4	ps_a	Preparation state for action a	
X_5	es_a	Execution state for action a	
X_6	ss_b	Sensor state for body state b	
X_7	srs_b	Sensory representation state for body sate b	
X_8	fs_b	Feeling state for body state b	
X_9	ps_b	Preparation state for body state b	
X_{10}	es_b	Expression execution state for body state b	
X_{11}	bs_-	Belief state for negative belief $-$	
X_{12}	bs_+	Belief state for positive belief $+$	
X_{13}	$\mathrm{cs}_{\mathrm{reapp}}$	Control state for reappraisal	
X_{14}	$\mathrm{cs}_{\mathrm{sup}}$	Control state for suppression	
X_{15}	$\mathrm{ms}_{\mathrm{dstrss}}$	Monitoring state for distress	
X_{16}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	First-order self-model state for connection weight $\boldsymbol{\omega}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{reapp}}}$	First-order self-model states
X_{17}	$\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	First-order self-model state for connection weight $\boldsymbol{\omega}_{\mathrm{fs}_b,\mathrm{cs}_{\mathrm{sup}}}$	

connected nodes automatically lead to strengthening of the connection. This form of mental plasticity or adaptation is represented by the self-model states $\mathbf{W}_{X,Y}$ representing the relevant connection weights used at the base level. The Hebbian learning, in this model, is taking place for the (monitoring) connections from fs_b to cs_{reapp} and fs_b to cs_{sup} in the base model, as these are the connections that activate the control states for the regulation strategies, which are assumed to relate to the PFC, and poor emotion regulation is often reported as relating to low activation levels within the PFC. The weights of these connections are represented by self-model states $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{reapp}}$ and $\mathbf{W}_{\mathrm{fs}_b,\mathrm{cs}_{sup}}$ respectively.

Note that, in this section, the adaptation itself is not adaptive; e.g., the speed factor of the adaptation (the adaptation rate) is constant. The type of adaptive learning which is based on metaplasticity is addressed in the next section through a second-order adaptive network model.

11.3.2.2 A Simulated Example Scenario Addressing Plasticity in Emotion Regulation

A simulated scenario obtained from the above first-order self-modeling network model is presented in this section. Figure 11.7 displays a number of most relevant base states for the simulated scenario and Fig. 11.8 displays the first-order self-model states, i.e., the **W**-states used for the adaptation.

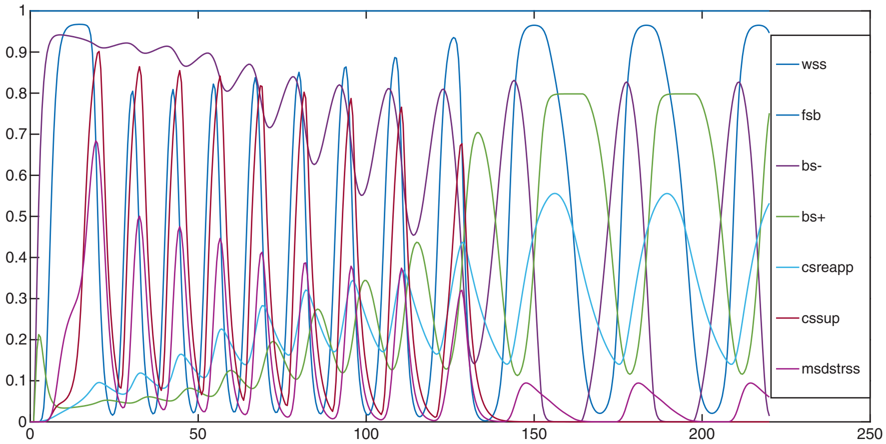

Fig. 11.7 Demonstration of the effective states of the base model over time

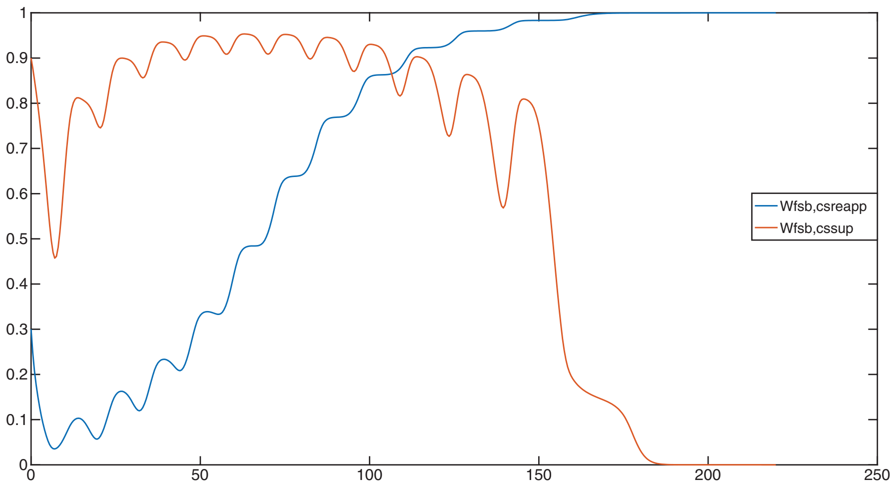

Fig. 11.8 First-order reified representation states over time

In Fig. 11.7 it can be seen that initially the negative belief bs_- gets activated which suppresses the positive belief bs_+. In the meanwhile, the negative feeling states fs_b also gets higher. The first half of the time scale represents the younger age of a person; therefore, he/she uses suppression. In case of activation of suppression, it can be observed that although the person suppresses the negative feelings, the negative belief bs_- still remains high. This reflects how suppression works: nothing changes for the belief. The fluctuation in the simulation results indicate the phenomenon that the regulation only takes place when there is a high level of emotion and as soon the emotion level is getting low, the regulation will stop so that the emotion may get higher again, and so on; this leads to emerging fluctuations. Another issue to be noted here is the monitoring state for distress ms_{dstrss}, which remains high, exactly as found in the literature in case of suppression. But this should decrease in case of reappraisal as per literature.

From the very beginning, it can be observed that the control state for reappraisal cs_{reapp} starts getting higher which represents a gradual shift in the choice of emotion regulation strategies based on underlying mechaisms that generate an emerging pattern over long time periods, so that from a correlational (but not causal) perspective it looks like an increase with age. Control state cs_{reapp} changes the beliefs which means increase in positive belief bs_+ and decrease of negative belief bs_-. This gradual increase finally enables the person to completely switch to reappraisal for the regulation of his emotions. An interesting thing here is the monitoring state for distress ms_{dstrss}, which remains very low exactly as relevant literature suggests in case of reappraisal.

Figure 11.8 gives insight into the states in the first-order self-model: $\mathbf{W}_{fs_b,cs_{sup}}$ and $\mathbf{W}_{fs_b,cs_{reapp}}$. In Fig. 11.8, initially $\mathbf{W}_{fs_b,cs_{sup}}$ is high which represents the use of expressive suppression in the younger age. Over time, $\mathbf{W}_{fs_b,cs_{reapp}}$ increases slowly and gradually until it reaches 1. It can be seen that as $\mathbf{W}_{fs_b,cs_{reapp}}$ increases, $\mathbf{W}_{fs_b,cs_{sup}}$ decreases until it reaches 0. This represents the shift taking place in choice of emotion regulation strategies that emerges over time while age is increasing.

11.4 Higher-Order Adaptation in Emotion Regulation

11.4.1 Metaplasticity in Emotion Regulation

Whether and to what extent plasticity as described above actually takes place is controlled by a form of *metaplasticity*; e.g., (Abraham & Bear, 1996; Garcia, 2002; Magerl et al., 2018; Robinson et al., 2016; Sehgal et al., 2013; Sjöström et al., 2008). For example, according to Robinson and his collogues ((Robinson et al., 2016), p. 2) the following compact quote indicates that due to stimulus exposure, the adaptation speed will increase:

> 'Adaptation accelerates with increasing stimulus exposure'

Similarly, a principle for modulation of persistence of learnt effects can be obtained:

> 'Stimulus exposure modulates persistence of adaptation'

Depending on further context factors, this can be applied in different ways. Reduced persistence can be used in order to be able to get rid of earlier learnt connections that are not effective anymore. However, enhanced persistence can be used to keep what has been learnt. In a similar direction ((Sjöström et al., 2008), p. 773) it is more generally discussed how it depends on the circumstances when the extent of plasticity is or should be high and when it is or should be low in favour of stability:

> 'The Plasticity Versus Stability Conundrum'

All the above are examples of principles describing metaplasticity, which can be considered adaptation of adaptation or second-order adaptation.

Within the cognitive neuroscience literature, Long-Term Potentiation (LTP) is a term used for activity-dependent persistent strengthening of a synapse which plays very important role in long term memory formation and cognitive processing. These patterns produce long lasting increase in signal transmission between two neurons. Opposite of LTP is LTD i.e. long-term depression which causes long lasting decrease in the synaptic strength (Vose & Stanton, 2017). According to (Vose & Stanton, 2017):

> 'Metaplasticity can be thought of as dynamic shifts in the set point for the amount of synaptic activation needed to produce the neurochemical events that induce either LTP or LTD, much like a climate set point determines the mean temperature fluctuations day-to-day.'

This can be seen as a higher-order form of synaptic plasticity. As also illustrated above, it can take place in various forms involving different mechanisms (Abraham & Bear, 1996).

Various examples of metaplasticity in terms of emotions can be found, for instance (Garcia, 2002; Vose & Stanton, 2017). Understanding of this plasticity regulation, has not only provided opportunities for better understanding of some of the mental processes and problems but also opened new vistas for treating those mental problems. According to Garcia (Garcia, 2002), due to high stress levels, a person's cognitive functioning gets poor, and as a result of that the person is no more able to adapt the emotion regulation in order to downregulate his stress: high stress levels slow down or block plasticity. He calls that the negative impact of metaplasticity or negative metaplasticity. Similarly, (Cibrian-Llanderal et al., 2018) also acknowledges the negative role of prolonged stress in cognitive functioning through high level of cortisol in the prefrontal cortex. In contrast, low levels of stress up-regulate this connectivity in the hippocampus which is called positive metaplasticity.

11.4.2 Simulated Scenarios for Metaplasticity in Emotion Regulation

The computational model and simulated scenario presented in this section illustrate the role of metaplasticity in emotion regulation. Again, the above case study will be used for this. First, in Sect. 11.4.2.1 the second-order adaptive computational network used is briefly explained, next, in Sect. 11.4.2.2 a simulated scenario is shown.

11.4.2.1 A Second-Order Adaptive Network Model for Metaplasticity in Emotion Regulation

The second-order adaptive network model used here is an extension of the first-order adaptive network model described in Sect. 11.3.2.1. The current section explains how this model can be extended by adding second-order self-model for the adaptation speed and for the persistence of the adaptation. In the first-order adaptive model, the learning speed and persistence both were constant. In the second-order adaptive network model, the characteristics of the learning are also adaptive, i.e., the speed and persistence characteristic of the learning can change. To achieve this, a second-order self-model is added covering states for these speed and persistence characteristics. The states in the second-order then represent these characteristics of the dynamics of the states in the first-order self-model. For instance, in our case, the newly added second-order self-model states will be responsible for the characteristics of the dynamics of $\mathbf{W}_{\text{fs}_b,\text{cs}_{sup}}$ and $\mathbf{W}_{\text{fs}_b,\text{cs}_{reapp}}$. This is achieved by adding a third plane on top of the model displayed in Fig. 11.6 with second-order self-model states such as $\mathbf{H}_{\mathbf{W}_{\text{fs}_b,\text{cs}_{reapp}}}$ and $\mathbf{M}_{\mathbf{W}_{\text{fs}_b,\text{cs}_{reapp}}}$, as shown in the upper plane in Fig. 11.9. Within the obtained second-order adaptive model Fig. 11.9, this upper plane represents the concept of metaplasticity where plasticity i.e. learning in our case (as modeled by the middle plane), itself is plastic to changes over time. The nomenclature of the states in the second-order self-model is given in Table 11.4.

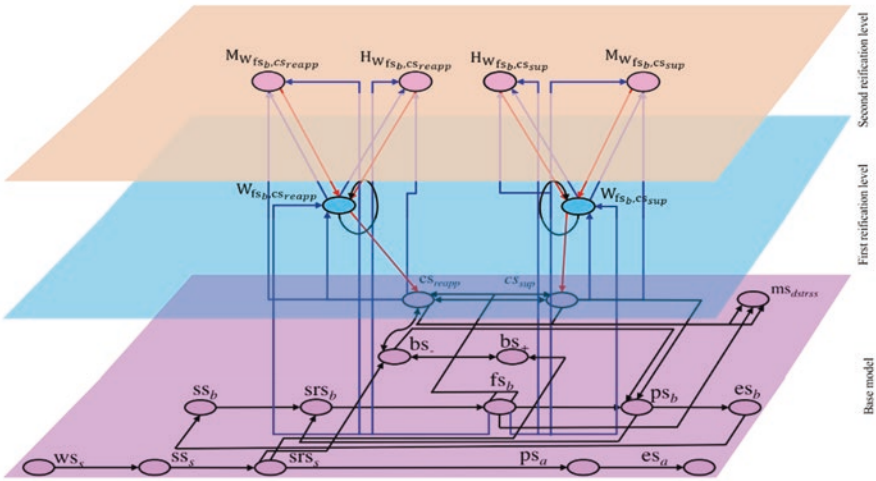

Fig. 11.9 Second-order adaptive network model for emotion regulation strategies over time

Table 11.4 Overview of the states of the second-order self-model

State	Explanation		Level
X_{18}	$\mathbf{M}_{\mathbf{W}_{\text{fs}_b,\text{cs}_{reapp}}}$	Second-order self-model state for persistence factor $\boldsymbol{\mu}$ for $\mathbf{W}_{\text{fs}_b,\text{cs}_{reapp}}$	Second-order self-model
X_{19}	$\mathbf{H}_{\mathbf{W}_{\text{fs}_b,\text{cs}_{reapp}}}$	Second-order self-model state for speed factor $\boldsymbol{\eta}$ for $\mathbf{W}_{\text{fs}_b,\text{cs}_{reapp}}$	
X_{20}	$\mathbf{H}_{\mathbf{W}_{\text{fs}_b,\text{cs}_{sup}}}$	Second-order self-model state for speed factor $\boldsymbol{\eta}$ for $\mathbf{W}_{\text{fs}_b,\text{cs}_{sup}}$	
X_{21}	$\mathbf{M}_{\mathbf{W}_{\text{fs}_b,\text{cs}_{sup}}}$	Second-order self-model state for persistence factor $\boldsymbol{\mu}$ for $\mathbf{W}_{\text{fs}_b,\text{cs}_{sup}}$	

Now, as this learning itself can change over time, for instance, increase or decrease, or maybe some of the learned experiences are retained for longer time and some are retained for shorter time. This indeed realizes forms of metaplasticity and is represented in the second-order self-model taking care of second-order adaptation. The speed factor is represented by the **H-**states and the persistence factor is represented by the **M-**states. For instance, the speed and persistence factor adaptation for $\mathbf{W}_{fs_b,cs_{reapp}}$ are represented by $\mathbf{H}_{\mathbf{W}_{fs_b,cs_{reapp}}}$ and $\mathbf{M}_{\mathbf{W}_{fs_b,cs_{reapp}}}$, and $\mathbf{H}_{\mathbf{W}_{fs_b,cs_{sup}}}$ and $\mathbf{M}_{\mathbf{W}_{fs_b,cs_{sup}}}$, respectively.

An overview of this second-order adaptive network and a full specification is given in Appendixes 2 and 3. This specification is essential for reproducibility of the results shown in this section. For a more detailed study, the concepts can be accessed at (Treur, 2020a, b).

11.4.2.2 A Simulated Example Scenario for Metaplasticity in Emotion Regulation

Inspiration for what is presented in the current section mainly comes from (Gao et al., 2019; Ullah et al., 2020a). The model presented here focuses on shifts for the choice in emotion regulation strategies that emerge over time. Table 11.8 in Appendix 2 provides the initial values of the states of the model.

Figure 11.10 depicts the entire simulated scenario showing all base states involved in the process. This shows a scenario where a person initially uses expressive suppression for his emotion regulation in young age andcognitive reappraisal when older. As mentioned above, the regularity of oscillation in the graphs indicates the fact that the emotion regulation strategies only get activated when the person experiences some negative emotions. Once the emotion levels have been regulated, the strategy gets deactivated. This arousal and regulation of negative emotions and the activation and deactivation of the strategies generate this emerging fluctuation in the graphs. For better analysis of this phenomenon, Fig. 11.11 presents only the key base states involved in this process.

Figures 11.7 and 11.11 display a similar scenario where in the latter there is no metaplasticity: the only difference is that the speed and persistence factors are constant in the latter case while it's adaptive in the former case. When compared to each other, it is clearly visible that in case of adaptive speed factor we have an extra handle to control the speed of the learning/first-order adaptation. This is also closer to the real-world examples.

As above, Figs. 11.8 and 11.12 also display the same states i.e. the **W-**states for the first-order adaptation. The difference here again is that in case of adaptive speed and persistence factors, we can change the characteristics of the first-order adaptation easily and therefore the simulation outcomes are more in our control and realistic.

Figure 11.13 is the representation of the second-order self-model states. These states are $\mathbf{H}_{\mathbf{W}_{fs_b,cs_{reapp}}}$, $\mathbf{M}_{\mathbf{W}_{fs_b,cs_{reapp}}}$ and $\mathbf{H}_{\mathbf{W}_{fs_b,cs_{sup}}}$, $\mathbf{M}_{\mathbf{W}_{fs_b,cs_{sup}}}$ which represent the speed

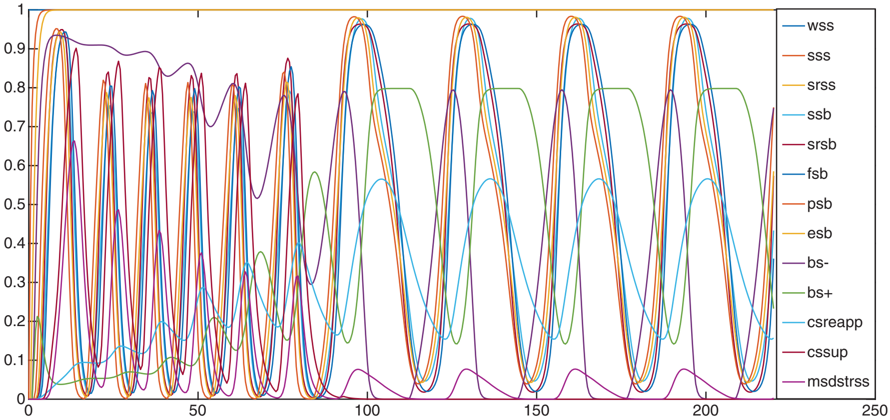

Fig. 11.10 Base states showing switching from Suppression to Reappraisal over time using metaplasticity

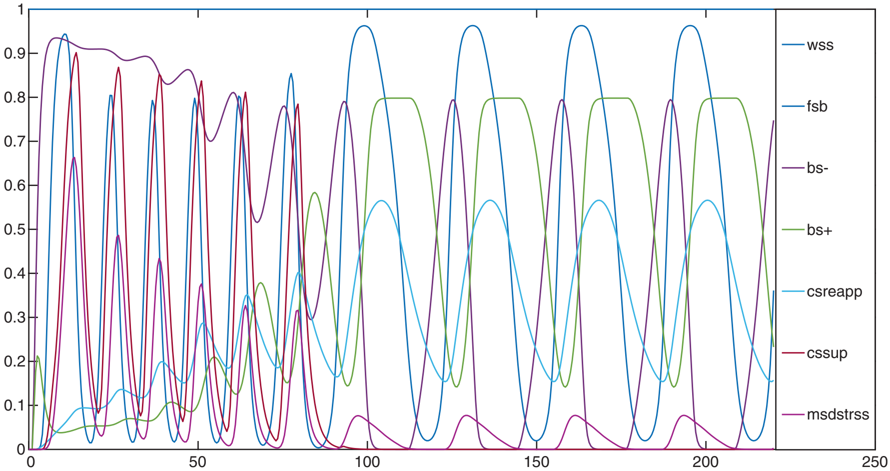

Fig. 11.11 The effective base states over time using metaplasticity

and the persistence factors of $\mathbf{W}_{\text{fs}_b, \text{cs}_{reapp}}$ and $\mathbf{W}_{\text{fs}_b, \text{cs}_{sup}}$, respectively. It can be observed that initially the speed and persistence factors of $\mathbf{W}_{\text{fs}_b, \text{cs}_{sup}}$ are quite high but this starts decreasing and hits zero once the speed and persistence factor of $\mathbf{W}_{\text{fs}_b, \text{cs}_{reapp}}$ reaches 1. This happens because of the shift that's taking place from suppression to reappraisal as a person grows. This phenomenon represents metaplasticity as defined in the relevant literature.

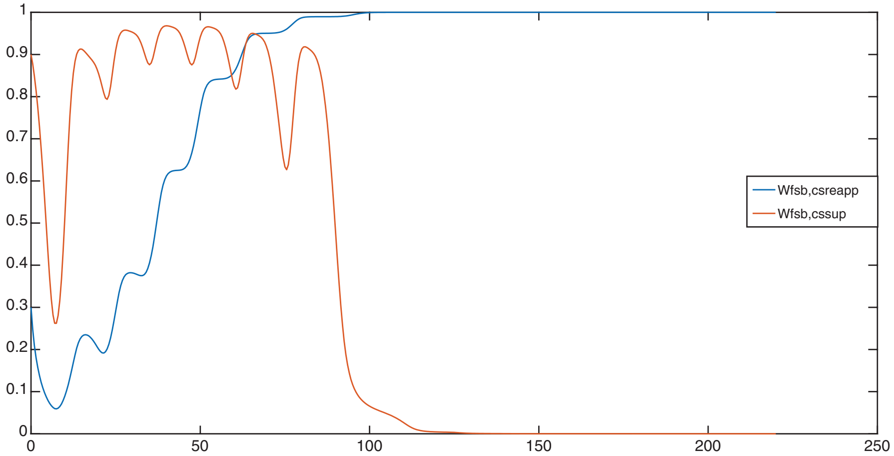

Fig. 11.12 First-order self-model states over time using metaplasticity

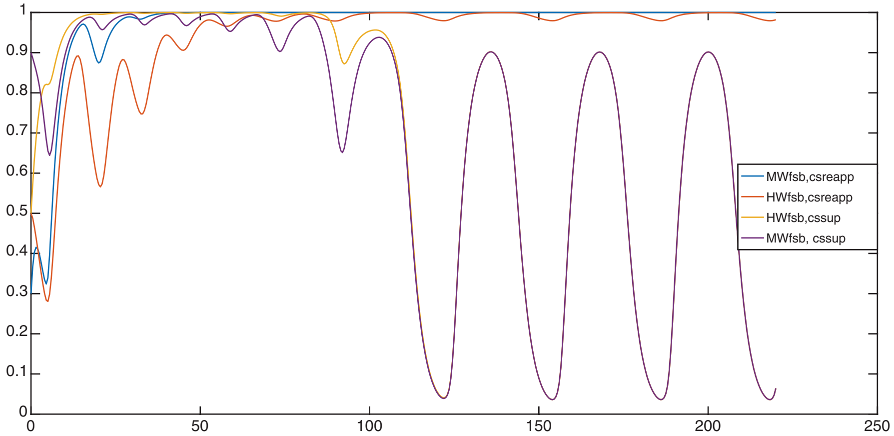

Fig. 11.13 Second-order self-model states for adaptation speed and persistence factors

11.5 Summary

In this chapter, the focus was on the computational analysis of emotion regulation specifically concerning flexibility and adaptivity. The concept of flexibility in emotion regulation strategies has recently gained momentum, with various studies yielding findings that support this notion. It is clear that specific strategies are not inherently adaptive or maladaptive, given that research has found that each strategy has the capacity to outclass other strategies in various situations. An important question is which strategy is used for which situation.

The answer to this question may lie in a broader repertoire with capabilities of decision making and analysis. A person with a broader repertoire of strategies has edge over a person using just a few strategies irrespective of the situation. For this purpose, the right decisions need to be taken for which strategy to use. This continuous adaptation of regulation and decision making also enables the person to know which strategy to use in which situation over longer period of time. This process of plasticity is taking place from very early life. In addition, plasticity of plasticity, also called metaplasticity, occurs, which adds control to the adaptation process.

These highly dynamic concepts have been modeled using a network-oriented modeling approach based on self-modeling temporal-causal networks (Treur, 2020a). This approach can easily be used for modeling any temporal phenomenon, such as the dynamics of emotions, desires and any other mental states. Moreover, the concepts of plasticity and metaplasticity can very easily and efficiently be modeled by using this approach. Apart from giving deep insight into complex phenomenon through the simulation results, this approach can model a very wide variety of complex problems.

The models presented in this chapter focus on the choice for using a certain emotion regulation strategy depending on specific circumstances, in line with studies like (Sheppes, 2014; Sheppes et al., 2011) where flexibility in emotion regulation strategies is the main concern. However, besides the question which strategy to use in which situation, in many cases, simply choosing an emotion regulation strategy is not enough to ensure its implementation. A chosen strategy can run into difficulties. Therefore, as a next challenge for future research, we aim to consider recent findings on maintaining a strategy, for instance, as addressed in (Gallo et al., 2009; Webb et al., 2012b). This has further been explored in (Pruessner et al., 2020) wherein selection and maintenance of a strategy has been differentiated. This means that a strategy, once chosen, has to be shielded against interference from other strategies and difficulties.

11.6 Further Reading

A preliminary version of part of this work was published in (Ullah & Treur, 2020b; Ullah et al., 2020b). Moreover, for more study about computational modeling of emotion regulation see, (Ullah & Treur, 2020c, d). For further literature on flexibility in emotion regulation, see, for example, (Cheng, 2001; Cheng et al., 2014; Troy et al., 2013). Also literature such as this can provide inspiration for further development of computational models for emotion regulation by addressing other factors that for the sake of simplicity have been left out of consideration in this chapter.

Appendix 1: Network-Oriented Modeling

Network-Oriented Modeling Based on Temporal-Causal Networks

All the modeling concepts used in this chapter are based on Network-Oriented Modeling by self-modeling temporal-causal networks (Treur, 2020a), see also (Treur, 2016). An overview of the basis for this modeling approach are the network characteristics for connectivity, aggregation and timing presented in Table 11.1. A phenomenon is represented in a network form which consists of nodes with activation levels that vary over time. Each node Y, also called state, has incoming connections from some other states X through connections with weights, which defines the causal impact of such a state X on state Y over time. A temporal-network model can be represented as a labelled graph for its network characteristics in which:

- **Connectivity characteristics**
- Each connection carries some *connection weight* from one state to another called *impact* represent by $\boldsymbol{\omega}_{X,Y.}$
- **Aggregation characteristics**
- There's some way to *aggregate multiple impacts* $\boldsymbol{\omega}_{X,Y}X(t)$ from some states X on a state Y by a combination function $\mathbf{c}_Y(..)$.
- **Timing characteristics**
- There's a notion of *speed of change* of each state to define how faster a state changes because of the incoming impact (speed factor $\boldsymbol{\eta}_Y$).

A temporal-causal network is fully defined by these three types of characteristics, which in a canonical manner define the numerical representation of the model; see Table 11.1 for more explanation of the terms and for these numerical representations. A dedicated software environment takes as input the above network characteristics and automatically (and hidden for the modeler) generates a numerical representation as described in the lower part of Table 11.5.

This approach provides a library of currently 40 combination functions for the aggregation of multiple (incoming) causal impacts. Apart from the available combination functions, an option is provided to easily create any function compositions of any of the available functions, and if that is still not enough, any own-defined functions can also be added to the library. This makes the technique even more flexible and user friendly. All software components, including the library, can be freely downloaded from URL https://www.researchgate.net/project/Network-Oriented-Modeling-Software.

Table 11.5 Basics of a temporal-causal network model

Concept	Conceptual representation	Explanation
States and connections	X, Y, $X \rightarrow Y$	Describes the nodes and links of a network structure (e.g., in graphical or matrix form)
Connection weight	$\boldsymbol{\omega}_{X,Y}$	The *connection weight* $\boldsymbol{\omega}_{X,Y}$ usually in [−1, 1] represents the strength of the causal impact of state X on state Y through connection $X \rightarrow Y$
Aggregating multiple impacts on a state	$\mathbf{c}_Y(..)$	For each state Y a *combination function* $\mathbf{c}_Y(..)$ is chosen to combine the causal impacts of other states on state Y
Timing of the effect of causal impact	$\boldsymbol{\eta}_Y$	For each state Y a *speed factor* $\boldsymbol{\eta}_Y \geq 0$ is used to represent how fast a state is changing upon causal impact
Concept	**Numerical representation**	**Explanation**
State values over time t	$Y(t)$	At each time point t each state Y in the model has a real number value, usually in [0, 1]
Single causal impact	$\mathbf{impact}_{X,Y}(t) = \boldsymbol{\omega}_{X,Y}\, X(t)$	At t state X with a connection to state Y has impact on Y, using connection weight $\boldsymbol{\omega}_{X,Y}$
Aggregating multiple causal impacts	$\mathbf{aggimpact}_Y(t)$ $= \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t),\ldots,$ $\mathbf{impact}_{X_k,Y}(t))$ $= \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t),\, \ldots,\, \boldsymbol{\omega}_{X_k,Y}X_k(t))$	The aggregated causal impact of multiple states X_i on Y at t, is determind using combination function $\mathbf{c}_Y(..)$
Timing of the causal effect	$Y(t + \Delta t) = Y(t) +$ $\boldsymbol{\eta}_Y\, [\mathbf{aggimpact}_Y(t) - Y(t)]\, \Delta t$ $= Y(t) +$ $\boldsymbol{\eta}_Y\, [\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t),\, \ldots,$ $\boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)]\, \Delta t$	The causal impact on Y is exerted over time gradually, using speed factor $\boldsymbol{\eta}_Y$; here the X_i are all states with outgoing connections to state Y

Note that the numerical representation in the lower part of Table 11.1 fully describes the dynamics of the temporal-causal network in terms of the network structure characteristics. This formal numerical representation associates detailed mathematically defined semantics to any temporal-causal network and also allows to mathematically analyze how emergent network behaviour depends on network structure, as has been done in (Treur, 2020a), Chaps. 11–14.

Self-Models Representing Network Characteristics by Network States

As indicated above, 'network characteristics' and 'network states' are two distinct concepts for a network. Self-modeling or reification as described in detail in (Treur, 2020a) is a way to relate these distinct concepts to each other in an interesting and useful way. A *self-model* is making the implicit network characteristics (such as connection weights) explicit in the form of adding states for these characteristics and connections for these states; thus, the network gets an internal self-model of part of the network structure itself. In this way, by iteration different self-modeling levels can be created where network characteristics from one level relate to explicit states at a next level. Thus, an arbitrary number of self-modeling levels can be modeled, covering *second-order* or *higher-order* effects. More specifically, adding a self-model for a temporal-causal base network is done in the way that for some of the states Y of the base network and some of the network structure characteristics for connectivity, aggregation and timing (i.e., some from $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{j,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$), additional network states $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ (called *self-model states* or *reification states*) are introduced and connected to other states:

(a) **Connectivity self-model**

- Self-model states $\mathbf{W}_{X,Y}$ are added representing connectivity characteristics, in particular connection weights $\boldsymbol{\omega}_{X,Y}$

(b) **Aggregation self-model**

- Self-model states $\mathbf{C}_{j,Y}$ are added representing aggregation characteristics, in particular combination function weights $\boldsymbol{\gamma}_{j,Y}$
- Self-model states $\mathbf{P}_{i,j,Y}$ are added representing aggregation characteristics, in particular combination function parameters $\boldsymbol{\pi}_{i,j,Y}$

(c) **Timing self-model**

- Self-model states $\mathbf{H}_Y$ are added representing timing characteristics, in particular speed factors $\boldsymbol{\eta}_Y$

The notations $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ for the self-model states indicate the referencing relation with respect to the characteristics $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{j,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$: here $\mathbf{W}$ refers to $\boldsymbol{\omega}$, $\mathbf{C}$ refers to $\boldsymbol{\gamma}$, $\mathbf{P}$ refers to $\boldsymbol{\pi}$, and $\mathbf{H}$ refers to $\boldsymbol{\eta}$, respectively. For the processing, these self-model states define the dynamics of any state Y in a canonical manner according to the equations in the bottom row of Table 11.5 whereby the values of $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{j,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$ are replaced by the state values of $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ at time t, respectively. To model certain adaptation principles by a self-modeling network, the dynamics of each self-model state itself and it effect on another state are specified for one of the three general types of network structure characteristics *connectivity* (a), *aggregation* (b), and *timing* (c), also mentioned above:

(a) **Connectivity for the self-model states in a self-modeling network**
For the self-model states their *connectivity* in terms of their incoming and outgoing connections has two different functions:

- **Effectuating its special effect from its specific role**

- The *outgoing downward causal connections* from the self-model states $\mathbf{W}_{X,Y}$, $\mathbf{C}_{j,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ to state Y represent the specific causal impact (its *special effect* from its specific *role*) each of these self-model states has on Y. These downward causal impacts are standard per role, and make that the adaptive values $\mathbf{W}_{X,Y}(t)$, $\mathbf{C}_{j,Y}(t)$, $\mathbf{P}_{i,j,Y}(t)$, $\mathbf{H}_Y(t)$ are used for the adaptive characteristics of the base network in (9).

- **Indicating the input for the adaptation principle as specified in (b)**

- The *incoming upward or leveled connections* to a self-model state are used to specify the *input* needed for *the particular adaptation principle* that is addressed.

(b) **Aggregation for the self-model states in a self-modeling network**

For the self-model states their aggregation characteristics have one main aim:

- **Expressing the aggregation adaptation principle by a mathematical function**

- For the *aggregation* of the incoming causal impacts for a self-model state, provided as indicated in (a), a specific combination function is chosen *to express the adaptation principle* in a declarative mathematical manner.

(c) **Timing for the self-model states in a self-modeling network**

For the self-model states their timing characteristics have one main aim:

- **Expressing the timing adaptation principle by a number**

- Finally, like any other state self-model states have their own *timing* in terms of speed factors. These speed factors are used as the *means to express the adaptation speed*.

An example of an aggregation self-model state $\mathbf{P}_{i,j,Y}$ for a combination function parameter $\boldsymbol{\pi}_{i,j,Y}$ is for the excitability threshold $\boldsymbol{\tau}_Y$ of state Y, which is the second parameter of a logistic sum combination function; then $\mathbf{P}_{i,j,Y}$ is usually indicated by $\mathbf{T}_Y$, where $\mathbf{T}$ refers to $\boldsymbol{\tau}$. The network constructed by the addition of a self-model to a base network is called a *self-modeling network* or a *reified network* for this base network. This constructed network is also a temporal-causal network model itself, as has been shown in (Treur, 2020a), Ch 10; for this reason, this construction can easily be applied iteratively to obtain multiple levels or orders of self-models, in which case the resulting network is called a *multi-level* or *multi-order* or *higher-order self-modeling network* or *reified network*.

Appendix 2: Tables

In Table 11.6 a state can either have value of scaling factor (λ) for which scale sum function has been used or it can have values for steepness (σ) and threshold (τ) for which alogistic combination function has been used.

Table 11.6 Values used for alogistic, scaled-sum combination functions and speed factor

state	λ	τ	σ	η	state	τ	σ	η
ws_s	0.94	0	0	0.1	ms_2	0.5	50	0.5
ss_s	0	0	0	0.5	$bs_{(-)c.p}$	0.1	50	0.5
ss_b	0	0	0	0.5	$bs_{(+)c.p}$	0.5	17	0.5
srs_s	1	0	0	0.5	cs_{reapp}	0.5	8	0.15
srs_b	1.4	0	0	0.5	$cs_{a.d}$	0.85	12	0.2
bs_-	0.91	0	0	0.5	$cs_{s.m}$	0.85	12	0.3
bs_+	0	0.1	10	0.5	cs_{sup}	0.5	6	0.15
ps_b	1.8	0	0	0.5	ps_a	0.6	5	0.5
es_b	0.98	0	0	0.5	$ps_{a.d}$	0	0	0.3
fs_b	1	0	0	0.5	es_a	0.5	3	0.5
ms_1	0	0.1	5	0.5	$es_{a.d}$	0	0	0.3

Table 11.7 Values used for connection weights

Connection	Weight	Connection	Weight	Connection	Weight	Connection	Weight
$\omega_{wss,\ wss}$	0.95	$\omega_{bs+,\ bs-}$	−0.4	$\omega_{csreapp,\ css.m}$	−1	$\omega_{fsb,\ ms1}$	0.5
$\omega_{wss,\ sss}$	1	$\omega_{ms1,\ csreapp}$	0.2	$\omega_{csreapp,\ cssup}$	−1	$\omega_{fsb,\ ms2}$	0.8
$\omega_{sss,\ srss}$	1	$\omega_{ms1,\ cssup}$	0.4	$\omega_{csa.d,\ psa.d}$	1	$\omega_{fsb,\ bs(-)c.p}$	0.5
$\omega_{ssb,\ srsb}$	0.7	$\omega_{ms2,\ ms1}$	−1	$\omega_{csa.d,\ css.m}$	−1	$\omega_{fsb,\ bs(+)c.p}$	0.5
$\omega_{srss,\ bsc-}$	0.9	$\omega_{ms2,\ csa.d}$	0.35	$\omega_{csa.d,\ cssup}$	−1	$\omega_{fsb,\ psb}$	0.9
$\omega_{srss,\ bsc+}$	0.4	$\omega_{ms2,\ css.m}$	0.5	$\omega_{css.m,\ psa}$	0.8	$\omega_{psa,\ esa}$	0.5
$\omega_{srss,\ psa}$	0.3	$\omega_{bs(-)c.p,\ bs(+)c.p}$	−1	$\omega_{css.m,\ esa}$	0.8	$\omega_{psb,\ srsb}$	0.75
$\omega_{srsc.p,\ bs(-)c.p}$	−1	$\omega_{bs(-)c.p,\ cssup}$	0.3	$\omega_{css.m,\ csreapp}$	−1	$\omega_{psb,\ esb}$	1
$\omega_{srsc.p,\ bs(+)c.p}$	1	$\omega_{bs(-)c.p,\ csa.d}$	0.6	$\omega_{css.m,\ csa.d}$	−1	$\omega_{psa.d,\ esa.d}$	1
$\omega_{srsb,\ fsb}$	1	$\omega_{bs(+)c.p,\ bs(-)c.p}$	−1	$\omega_{cssup,\ psb}$	−1	$\omega_{esa,\ wss}$	−0.5
$\omega_{bs-,\ bs+}$	−0.4	$\omega_{bs(+)c.p,\ css.m}$	0.5	$\omega_{cssup,\ esb}$	−0.2	$\omega_{esb,\ ssb}$	1
$\omega_{bs-,\ csreapp}$	0.05	$\omega_{bs(+)c.p,\ csreapp}$	0.33	$\omega_{cssup,\ csreapp}$	−1	$\omega_{esa.d,\ srss}$	0.63
$\omega_{bs-,\ psb}$	1	$\omega_{csreapp,\ bs-}$	−0.35	$\omega_{cssup,\ csa.d}$	−1		

Table 11.8 Initial values of the states

State	ws_s	All other base states	$\mathbf{W}_{fs_b,cs_{reapp}}$	$\mathbf{W}_{fs_b,cs_{sup}}$	$\mathbf{H}_{\mathbf{W}_{fs_b,cs_{reapp}}}$	$\mathbf{H}_{\mathbf{W}_{fs_b,cs_{sup}}}$	$\mathbf{M}_{\mathbf{W}_{fs_b,cs_{reapp}}}$	$\mathbf{M}_{\mathbf{W}_{fs_b,cs_{sup}}}$
Initial value	1	0	0.3	0.9	0.5	0.5	0.9	0.9

11.7 Appendix 3: Role Matrices

The red cells with X_i in them represent the adaptive dynamics of that connections in matrices **mcw,mcfp** and **ms**. For instance, X_{16} in the red cell in **mcw** refers to $\mathbf{W}_{fs_b,cs_{reapp}}$ and this state represent the adaptivity taking place at connection from fs_b to cs_{reapp}. Similarly, the X_{18} and X_{19} in mcfp and ms represents the persistence and speed factor of $\mathbf{W}_{fs_b,cs_{reapp}}$, respectively (Figs. 11.14 and 11.15).

mb connectivity: base connectivity		1	2	3
X_1	ws_s	X_1		
X_2	ss_s	X_1		
X_3	srs_s	X_2		
X_4	ps_a	X_3		
X_5	es_a	X_4		
X_6	ss_b	X_{10}		
X_7	srs_b	X_9	X_6	
X_8	fs_b	X_7		
X_9	ps_b	X_8	X_{11}	X_{14}
X_{10}	es_b	X_9		
X_{11}	bs_-	X_3	X_{13}	X_{12}
X_{12}	bs_+	X_3	X_{11}	
X_{13}	cs_{reapp}	X_8	X_{11}	
X_{14}	cs_{sup}	X_8	X_{13}	
X_{15}	ms_{dstrss}	X_8	X_{13}	X_{14}
X_{16}	$\mathbf{W}_{fs_b,cs_{reapp}}$	X_8	X_{13}	X_{16}
X_{17}	$\mathbf{W}_{fs_b,cs_{sup}}$	X_8	X_{14}	X_{17}
X_{18}	$\mathbf{MW}_{fs_b,cs_{reapp}}$	X_8	X_{13}	X_{16}
X_{19}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	X_8	X_{13}	X_{16}
X_{20}	$\mathbf{HW}_{fs_b,cs_{sup}}$	X_8	X_{14}	X_{17}
X_{21}	$\mathbf{MW}_{fs_b,cs_{sup}}$	X_8	X_{14}	X_{17}

mcw connectivity: connection weights		1	2	3
X_1	ws_s	1		
X_2	ss_s	1		
X_3	srs_s	1		
X_4	ps_a	0.1		
X_5	es_a	0.2		
X_6	ss_b	1		
X_7	srs_b	0.5	0.15	
X_8	fs_b	1		
X_9	ps_b	0.4	0.5	-0.9
X_{10}	es_b	1		
X_{11}	bs_-	0.6	-0.7	-0.4
X_{12}	bs_+	0.4	-0.4	
X_{13}	cs_{reapp}	X_{16}	0.4	
X_{14}	cs_{sup}	X_{17}	-0.6	
X_{15}	ms_{dstrss}	0.4	-0.4	0.4
X_{16}	$\mathbf{W}_{fs_b,cs_{reapp}}$	1	1	1
X_{17}	$\mathbf{W}_{fs_b,cs_{sup}}$	1	1	1
X_{18}	$\mathbf{MW}_{fs_b,cs_{reapp}}$	1	1	1
X_{19}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	1	1	1
X_{20}	$\mathbf{HW}_{fs_b,cs_{sup}}$	0.6	0.8	0.8
X_{21}	$\mathbf{MW}_{fs_b,cs_{sup}}$	0.6	0.8	0.5

Box 1 Role matrices for connectivity

mcfw aggregation: combination function weights		1 alogistic	2 hebb	3 id
X_1	ws_s			1
X_2	ss_s			1
X_3	srs_s			1
X_4	ps_a			1
X_5	es_a			1
X_6	ss_b			1
X_7	srs_b	1		
X_8	fs_b			1
X_9	ps_b	1		
X_{10}	es_b			1
X_{11}	bs_-	1		
X_{12}	bs_+	1		
X_{13}	cs_{reapp}	1		
X_{14}	cs_{sup}	1		
X_{15}	ms_{dstrss}	1		
X_{16}	$\mathbf{W}_{fs_b,cs_{reapp}}$		1	
X_{17}	$\mathbf{W}_{fs_b,cs_{sup}}$		1	
X_{18}	$\mathbf{MW}_{fs_b,cs_{reapp}}$	1		
X_{19}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	1		
X_{20}	$\mathbf{HW}_{fs_b,cs_{sup}}$	1		
X_{21}	$\mathbf{MW}_{fs_b,cs_{sup}}$	1		

mcfp aggregation: combination func-tion parameters		1 alogistic σ	1 alogistic τ	2 hebb μ	id
X_1	ws_s				1
X_2	ss_s				1
X_3	srs_s				1
X_4	ps_a				1
X_5	es_a				1
X_6	ss_b				1
X_7	srs_b	10	0.3		
X_8	fs_b				1
X_9	ps_b	10	0.3		
X_{10}	es_b				1
X_{11}	bs_-	8	0.2		
X_{12}	bs_+	8	0.2		
X_{13}	cs_{reapp}	5	0.8		
X_{14}	cs_{sup}	12	0.2		
X_{15}	ms_{dstrss}	8	0.5		
X_{16}	$\mathbf{W}_{fs_b,cs_{reapp}}$			X_{18}	
X_{17}	$\mathbf{W}_{fs_b,cs_{sup}}$			X_{21}	
X_{18}	$\mathbf{MW}_{fs_b,cs_{reapp}}$	12	0.2		
X_{19}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	4	0.2		
X_{20}	$\mathbf{HW}_{fs_b,cs_{sup}}$	10	0.3		
X_{21}	$\mathbf{MW}_{fs_b,cs_{sup}}$	10	0.3		

ms timing: speed factors		η
X_1	ws_s	0
X_2	ss_s	1
X_3	srs_s	1
X_4	ps_a	1
X_5	es_a	1
X_6	ss_b	1
X_7	srs_b	1
X_8	fs_b	1
X_9	ps_b	1
X_{10}	es_b	1
X_{11}	bs_-	1
X_{12}	bs_+	1
X_{13}	cs_{reapp}	0.1
X_{14}	cs_{sup}	0.4
X_{15}	ms_{dstrss}	0.5
X_{16}	$\mathbf{W}_{fs_b,cs_{reapp}}$	X_{19}
X_{17}	$\mathbf{W}_{fs_b,cs_{sup}}$	X_{20}
X_{18}	$\mathbf{MW}_{fs_b,cs_{reapp}}$	0.3
X_{19}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	0.3
X_{20}	$\mathbf{HW}_{fs_b,cs_{sup}}$	0.3
X_{21}	$\mathbf{MW}_{fs_b,cs_{sup}}$	0.3

Box 2 Role matrices for aggregation and timing

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