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Chapter 13

Taking Control of Your Bonding: Controlled Social Network Adaptation Using Mental Models



Jan Treur

Abstract In this chapter, the role of subjective elements and control in social network adaptation is analysed computationally. In particular, it is analysed: (1) how the coevolution of social contagion and bonding by homophily may be controlled by the persons involved, and (2) how subjective representation states (e.g., what they know) can play a role in this coevolution and its control. To address this, a second-order adaptive social network model is presented in which persons do have a form of control over the coevolution process, and, in relation to this, their bonding depends on their subjective representation states about themselves and about each other, and social contagion depends on their subjective representation states about their connections.

Keywords Controlled social network adaptation · Bonding by homophily

13.1 Introduction

Social networks often do not only show dynamics *within* the network but also dynamics *of* the network, where the latter is also called network adaptation. These combined dynamics are sometimes referred to as coevolution of the network states and the network connections. An often studied case for social networks is the coevolution of social contagion (for the dynamics of the network nodes or states) and bonding by homophily (for the dynamics of the weights of the network connections). The bonding by homophily adaptation principle expresses how ‘being alike’ strengthens the connection between two persons, also explained as ‘birds of a feather flock together’; e.g., (McPherson et al. 2001; Pearson et al. 2006). On the other hand, social contagion makes that network states affect each other through their connections, which implies that the stronger two persons are connected, the more they will become alike (Levy and Nail 1993). This makes circular, reciprocal causal relations

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between the two processes. It has been found in simulations that, as in the real world, the emerging behaviour of adaptive network models based on coevolution of these two processes, often shows a form of clustering, segregation or community formation; e.g., (Blankendaal et al. 2016; Boomgaard et al. 2018; Holme and Newman 2006; Sharpanskykh and Treur 2014; Treur 2017, 2019; Vazquez 2013; Vazquez et al. 2007).

Usually, in literature as mentioned, these social processes are considered without taking into account subjective elements for the persons involved. For example, do the persons themselves actually know in how far they are alike? Do they *have* to know that to let the bonding work properly? Do they know their connections? Are persons able to have some control over their bonding? Or are they just will-less victims of objective social laws independent of what they know or what they want? Such subjective aspects are lacking in (computational) research on bonding by homophily as mentioned, as usually these coevolution processes are addressed exclusively from the perspective of an objective social world. Note that in other in Social Science literature such as (Casciaro et al. 1999; Krackhardt 1987; Vaisey and Lizardo 2010) from a wider perspective also the role of cognitive and cultural interpretation in social dynamics is emphasized.

In the current chapter, it is assumed that such subjective elements indeed do matter and it is analysed computationally how some of them can play their role in the coevolution process. More specifically, it is analysed: (1) how the coevolution of social contagion and bonding by homophily may be controlled by the persons involved, and (2) how subjective states representing what they know about themselves, about others and about their connections play a role in this coevolution and its control. To this end a second-order adaptive social network model has been developed in which persons have control over the coevolution process, and their bonding and social contagion depend on subjective representations of the involved persons about themselves and each other, and about their connections.

In the chapter, in Sect. 13.2 the higher-order adaptive network-oriented modeling approach from (Treur 2020) used is briefly explained. In Sect. 13.3 the designed second-order adaptive social network model is presented. Section 13.4 addresses simulation results for a case study on adaptation in tetradic relationships. Finally, Sect. 13.5 is a discussion section, where, among others, it is discussed how the model can predict that faking your properties can be an effective way to achieve a desired bonding.

13.2 Higher-Order Adaptive Network Models

In this section, the network-oriented modeling approach used is briefly introduced. Following Treur (2016, 2020b), a temporal-causal network model is characterised by:

- **Connectivity characteristics** Connections from a state X to a state Y and their weights $\omega_{X,Y}$

- **Aggregation characteristics** For any node Y , some combination function $\mathbf{c}_Y(\cdot)$ defines aggregation that is applied to the impacts $\omega_{X_i,Y}X_i(t)$ on Y from its incoming connections from states X_1, \dots, X_k
- **Timing characteristics** Each state Y has a speed factor η_Y defining how fast it changes for given causal impact

The following difference (or differential) equations that are useful for simulation purposes and also for analysis of temporal-causal networks incorporate these network characteristics $\omega_{X,Y}$, $\mathbf{c}_Y(\cdot)$, η_Y :

$$Y(t + \Delta t) = Y(t) + \eta_Y [\mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) - Y(t)] \Delta t \quad (13.1)$$

for any state Y and where X_1, \dots, X_k are the states from which it gets its incoming connections. Within the software environment described in (Treur 2020b), Chap. 9 a large number > 35 of useful combination functions are included in a combination function library. The three combination functions from this library used for states Y in the introduced network model are:

- the *Euclidean combination function* $\mathbf{eucl}_{n,\lambda}(V_1, \dots, V_k)$ defined by

$$\mathbf{eucl}_{n,\lambda}(V_1, \dots, V_k) = \sqrt[n]{\frac{V_1^n + \dots + V_k^n}{\lambda}} \quad (13.2)$$

where n is the order and λ a scaling factor and V_1, \dots, V_k are the impacts from the states from which the considered state Y gets incoming connections.

- the *advanced logistic sum combination function* $\mathbf{alogistic}_{\sigma,\tau}(V_1, \dots, V_k)$ defined by:

$$\mathbf{alogistic}_{\sigma,\tau_{\log}}(V_1, \dots, V_k) = \left[\frac{1}{1 + e^{-\sigma(V_1 + \dots + V_k - \tau_{\log})}} - \frac{1}{1 + e^{\sigma\tau_{\log}}} \right] (1 + e^{-\sigma\tau_{\log}}) \quad (13.3)$$

where σ is a steepness parameter and τ_{\log} a threshold parameter and V_1, \dots, V_k are the impacts from the states from which the considered state Y gets incoming connections

- the *simple linear homophily combination function* $\mathbf{slhomo}_{\alpha,\tau_{\text{homo}}}(V_1, V_2, W)$ defined by

$$\mathbf{slhomo}_{\alpha,\tau_{\text{homo}}}(V_1, V_2, W) = W + \alpha W(1 - W)(\tau_{\text{homo}} - |V_1 - V_2|) \quad (13.4)$$

where α is an amplification parameter and τ_{homo} the tipping point parameter and V_1, V_2 are a person's representations of the two persons' states involved and W represents the weight of their connection.

In Sect. 13.3, the combination function $\mathbf{eucl}_{n, \lambda}(\dots)$ be used to model social contagion and formation of internal state representations, $\mathbf{slhomo}_{\alpha, \tau_{\text{homo}}}(V_1, V_2, W)$ to model bonding based on homophily by internal connection weight representations, and $\mathbf{alogistic}_{\sigma, \tau_{\text{log}}}(\dots)$ to model control of the bonding. Note that the homophily tipping point τ_{homo} is the point where the difference between the states of the two individuals (represented by $|V_1 - V_2|$) turns an increase of bonding (outcome $> \mathbf{W}$) into a decrease (outcome $< \mathbf{W}$), and conversely.

The above concepts enable to design network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. Realistic network models are usually adaptive: often some of their network characteristics change over time. By using *self-modeling networks* (or *network reification*), a similar network-oriented conceptualisation can also be applied to *adaptive networks* to obtain a declarative description using mathematically defined functions and relations for them as well; see Treur (2020a, b). This works through the addition of new states to the network called *self-model states* (or *reification states*) which represent network characteristics by network states. If such self-model states are dynamic, they describe adaptive network characteristics. In a graphical 3D-format, such self-model states are depicted at a next level (*self-model level*), where the original network is at a *base level*. As an example, the weight $\omega_{X,Y}$ of a connection from state X to state Y can be represented (at a next self-model level) by a self-model state named $\mathbf{W}_{X,Y}$ (objective representation) or $\mathbf{RW}_{X,Y}$ (subjective representation). Similarly, all other network characteristics from $\omega_{X,Y}$, $\mathbf{c}_Y(\cdot)$, η_Y can be made adaptive by including self-model states for them.

As a self-modeling network model is also a temporal-causal network model itself, as has been proven in Treur (2020b), Chap. 10, this self-modeling construction can easily be applied iteratively to obtain multiple self-model levels. This can provide higher-order adaptive network models, and has turned out quite useful to model, for example, plasticity and metaplasticity as known from neuroscience, in the form of a second-order adaptive mental network with three levels, one base level and a first- and a second-order self-model level; e.g., (Abraham and Bear 1996; Magerl et al. 2018; Treur 2020b), Chap. 4. In the current chapter, multi-level network self-modeling will be applied for higher-order adaptive social network models in particular.

13.3 A Network Model for Controlled Social Network Adaptation

This section presents the introduced network model for controlled social network adaptation by using subjective representations. This network model integrates three types of interacting processes:

- The social network's within-network dynamics based on social contagion
- First-order social network adaptation based on bonding by homophily
- Second-order social network adaptation to control the network adaptation

The above three types of processes have been modeled by a second-order adaptive network architecture based on multi-level self-modeling as described in Sect. 13.2, with connectivity as depicted in Fig. 13.1. In this 3D picture, each of the three planes models one of the three types of processes mentioned above.

The types of states and connections used at and between the three levels within this network model are shown in Tables 13.1 and 13.2 Here A and B are variables over persons and Y is a type of state of a person, for example, how much the person likes to watch Netflix series. At the base level, social contagion is modelled by connections $S_{A,Y} \rightarrow S_{B,Y}$. Each person has subjective internal representation states of other persons' states Y (and the state of her or himself) and of his or her connections to others. This is modeled by the first-order self-model. A person B 's internal representation state for person A having state Y is modeled by state representation $RS_{A,B,Y}$. A person A 's subjective representation of his or her connection to B is modeled by connection weight representation $RW_{A,B,Y}$. There are two pathways that contribute to formation of state representations $RS_{A,B,Y}$. First, these representations can be

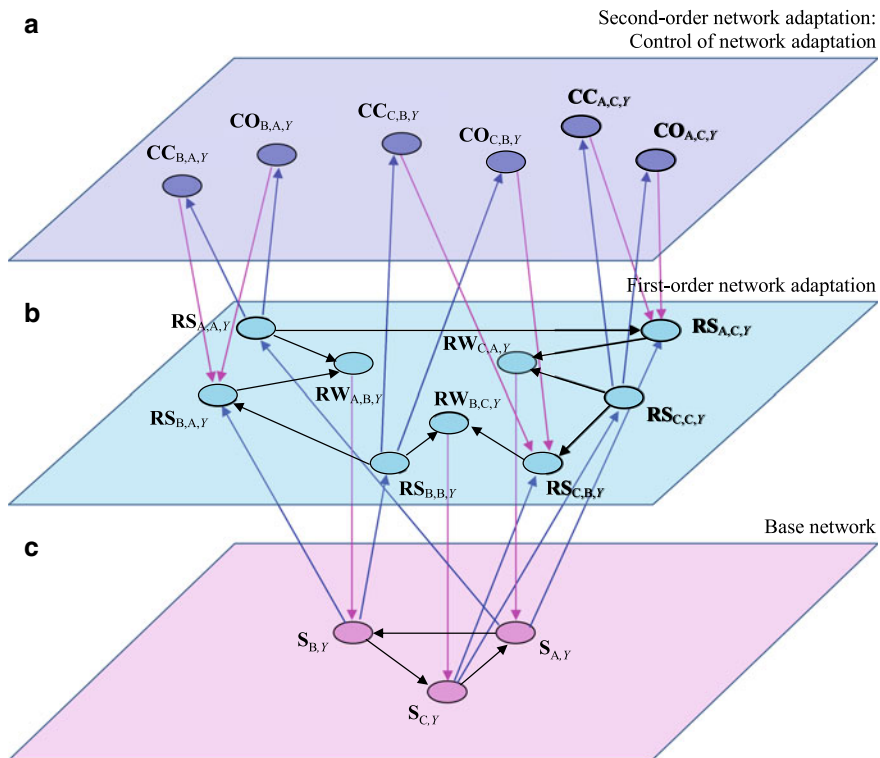


Fig. 13.1 Overview of the connectivity of the second-order adaptive social network model for three example persons A, B and C

Table 13.1 Types of states in the introduced controlled adaptive social network model

$S_{B,Y}$	Objective state Y of person B
$RS_{A,B,Y}$	Subjective representation of person B for state Y of person A
$RW_{A,B,Y}$	Subjective representation of person A for the connection weight from person A to person B
$CC_{A,B,Y}$	Control state for communication from A to B : representation of the weight of the connection from $RS_{A,A,Y}$ to $RS_{A,B,Y}$
$CO_{A,B,Y}$	Control state for observation by B : representation of the weight of the connection from $S_{A,Y}$ to $RS_{A,B,Y}$ for the state Y of A observed by B

communicated between persons. For example, if A communicates his or her subjective representation $RS_{A,A,Y}$ of the own state $S_{A,Y}$ to B , this is modeled by a connection $RS_{A,A,Y} \rightarrow RS_{A,B,Y}$. A second pathway for a person B to get information on person A 's state is through observation of $S_{A,Y}$ by B . This is modeled by a connection $S_{A,Y} \rightarrow RS_{A,B,Y}$.

As indicated, person A 's representation of her or his connection to person B is modeled by $RW_{A,B,Y}$. It is assumed that the adaptive change of the represented connections depends on the internal representation states $RS_{A,B,Y}$. As the changes considered here are based on a homophily principle for state Y , this adaptation is supported by connections $RS_{A,A,Y} \rightarrow RW_{A,B,Y}$ and $RS_{B,A,Y} \rightarrow RW_{A,B,Y}$. The connection representations $RW_{A,B,Y}$ in turn affect the social contagion within the social network, which is modeled by downward connections $RW_{A,B,Y} \rightarrow S_{B,Y}$.

To control the social network adaptation processes, two types of control actions are considered in particular:

- controlling the communication of state Y from person A to person B , modeled by control states $CC_{A,B,Y}$
- controlling the observation of state Y from person A by person B , modeled by control states $CO_{A,B,Y}$

Activation of a communication control state $CC_{A,B,Y}$ makes that the connection $RS_{A,A,Y} \rightarrow RS_{A,B,Y}$ from A 's state $RS_{A,A,Y}$ to B 's state $RS_{A,B,Y}$ gets a high value (1 or close to 1) so that the transfer of information by communication happens; this is modeled by connections $CO_{A,B,Y} \rightarrow RS_{A,B,Y}$. This can be considered as B asking A for the information about him or herself, upon which A communicates this information. Similarly, activation of an observation control state $CO_{A,B,Y}$ makes that the connection $S_{A,Y} \rightarrow RS_{A,B,Y}$ from A 's state $S_{A,Y}$ to B 's state $RS_{A,B,Y}$ gets a high value (1 or close to 1) so that the transfer of information by observation takes place; this is modeled by connections $CO_{A,B,Y} \rightarrow RS_{A,B,Y}$. As an example used in the case study in Sect. 13.4, the control states $CC_{A,B,Y}$ and $CO_{A,B,Y}$ themselves may become active depending on B 's state $RS_{B,B,Y}$; this is modeled by connections $RS_{B,B,Y} \rightarrow CO_{A,B,Y}$ and $RS_{B,B,Y} \rightarrow CO_{A,B,Y}$. But this can be addressed in many other ways as well, including externally determined control, for example, by enabling or allowing observation or communication (only) at specific time slots.

Table 13.2 Types of connections in the controlled adaptive social network model

Intralevel connections		
$S_{A,Y} \rightarrow S_{B,Y}$	Social contagion from A to B for state Y	
$RS_{A,A,Y} \rightarrow RS_{A,B,Y}$	Communication of $S_{A,Y}$ from A to B	
$RS_{A,A,Y} \rightarrow RW_{A,B,Y}$	Effect of state Y of A on bonding by homophily from A to B	
$RS_{B,A,Y} \rightarrow RW_{A,B,Y}$	Effect of state Y of B on bonding by homophily from A to B	
Interlevel connections		
$S_{A,Y} \rightarrow RS_{A,B,Y}$	Observation by B of A 's state Y	Upward from base level to first self-model level
$RW_{A,B,Y} \rightarrow S_{B,Y}$	Effectuation of base connection weights for social contagion from A to B	Downward from first self-model level to base level
$RS_{B,B,Y} \rightarrow CO_{A,B,Y}$	Observation control monitoring connections for B	Upward from first to second self-model level
$RS_{B,B,Y} \rightarrow CC_{A,B,Y}$	Communication control monitoring connections for B	
$CO_{A,B,Y} \rightarrow RS_{A,B,Y}$	Effectuation of control of observation of A by B	Downward from second to first self-model level
$CC_{A,B,Y} \rightarrow RS_{A,B,Y}$	Effectuation of control of communication from A by B	

13.4 Simulation for a Tetradic Relationship Example

In this section, a simulation of an example scenario will be discussed to illustrate the introduced second-order adaptive social network model. The example scenario describes an adaptive tetradic relationship configuration with initially two couples all four of which are friends: Mark and Dion, and Ann and Jenny. After the process described in the scenario they find themselves in a slightly changed configuration, where Mark and Jenny, and Dion and Ann have the stronger connections; see Fig. 13.2. This adaptation process takes place because Mark and Jenny realize that they have more in common with as an example used here their preference to watch Netflix series. Similarly, Dion and Ann realize that they also have more in common, in their case disliking watching Netflix series (and instead a preference for outdoor activities).

To specify a network model according to the approach from (Treur 2020b), as discussed in Sect. 13.2, three types of network characteristics are to be addressed: *connectivity*, *aggregation* and *timing* characteristics. They have been specified in role matrix format as shown in the Appendix Sect. 13.8 and used for the simulation discussed after. For the sake of simplicity, the subscript Y (which for the example stands for a preference to watch Netflix series) has been left out here. Role matrices indicate in rows successively for all network states, the factors that affect them from different roles. In role matrix **mb** (see Sect. 13.8), for each state it is indicated from which other states it has incoming connections from the same or a lower level. In the same box in role matrix **mcw**, it is indicated what are the connection weights for the connected states indicated in **mb**. If the connection weights are static, their static value is indicated in matrix **mb**, but if the connection weight is adaptive, the self-model state representing this weight is indicated, as in that case at each time point this is where the (dynamic) connection weight value can be found. This can be seen for all incoming connections for the first four states X_1 to X_4 , and for all incoming connections for the state representation states X_9 to X_{20} . Indicating these adaptive value representations, defines the downward connections of Fig. 13.1. Also the speed factors are shown in Sect. 13.8 (role matrix **ms**, which actually is a vector).

In the second box in Sect. 13.8, showing the aggregation characteristics, it can be seen which states use which combination functions (role matrix **mcfw**) and which parameter values for them (role matrix **mcfp**); also the initial values for the example simulation are shown here.

In Figs. 13.3 and 13.4 the simulation for the example scenario is shown. In Fig. 13.3



Fig. 13.2 Example scenario for a tetradic relationship configuration where initially M and D and J and A have strong connections and in the end M and J and D and A have the strong connections

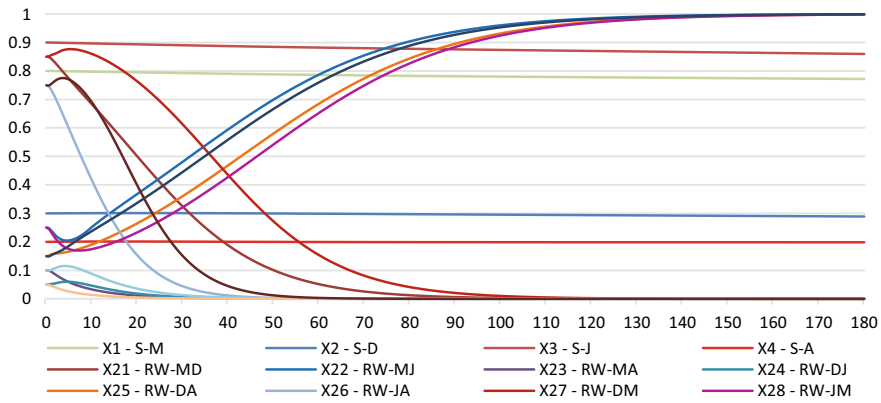


Fig. 13.3 Outcomes for the example scenario simulation: the changes in all relationships

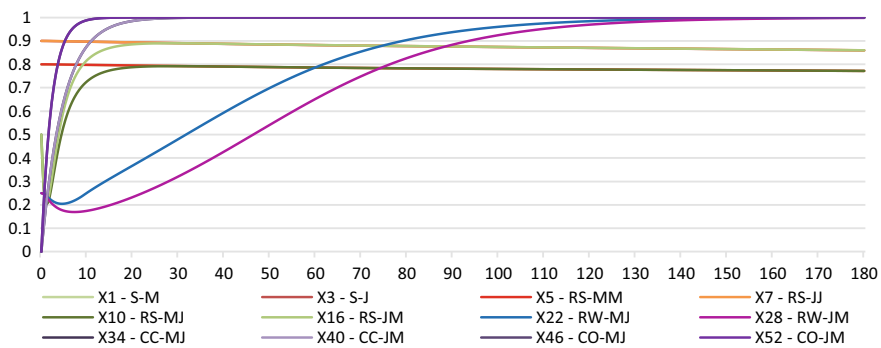


Fig. 13.4 The role of control and subjective states for the relationship between Mark and Jenny

the co-evolution of changing states and connection (self-model) representations is shown without showing the underlying personal state representations. Here the states S_A are slowly changing whereas the connection representations $RW_{A,B}$ are changing faster. It indeed can be seen that for Mark and Jenny both directional connection representations $RW_{M,J}$ and $RW_{J,M}$ start to increase from timepoint 5 resp. 10 on to finally end up at a value (close to) 1. Similarly, the connection representations $RW_{D,A}$ and $RW_{A,D}$ between Dion and Ann start to increase after time 5. In the same time period, the connection representations $RW_{M,D}$ and $RW_{D,M}$ between Mark and Dion and $RW_{J,A}$ and $RW_{A,J}$ between Jenny and Ann decrease to (close to) 0. All these changes are a consequence of the homophily principle, as the state values S_M and S_J for Mark and Jenny are close to each other (0.8 and 0.9), and S_D and S_A for Dion and Ann also (0.2 and 0.3); note that the tipping point for similarity set was 0.25, so (only) a difference < 0.25 is strengthening a relationship. In contrast, the values for Mark and Dion differ a lot (0.8 vs. 0.3), which is much higher than

the tipping point 0.25 and therefore has a decreasing effect on their relationship; the same pattern holds for Jenny and Ann.

Finally, in the right lower corner it can be seen that the other connection representations (for example, for Jenny and Dion) were already low and still became lower because of big differences in their states. It can be noted that all connection representations converge to 0 or 1, which shows that clustering (and segregation) takes place, where the emerging clusters are Mark-Jenny and Dion-Ann, whereas the initial configuration (approximately) had clusters Mark-Dion and Jenny-Ann (also see Fig. 13.2).

In Fig. 13.4, the focus is on the development of the connections between Mark and Jenny and in particular it zooms in on the role that is played by the control states $\mathbf{CC}_{A,B,Y}$ and $\mathbf{CO}_{A,B,Y}$ and the subjective representation states $\mathbf{RS}_{A,B,Y}$. The dark purple line that gets close to 1 before time 10 indicates the control states $\mathbf{CC}_{A,B,Y}$ for the communication between them, which makes that at that time their mutual communication channels $\mathbf{RS}_{A,A,Y} \rightarrow \mathbf{RS}_{A,B,Y}$ get weights close to 1. This implies that before time 10 they indeed both communicate to each other that they like watching Netflix series. These control states for the communication are triggered in this example scenario because each of them observes his or her own behaviour and therefore they form representations $\mathbf{RS}_{A,A}$ of their own states \mathbf{S}_A concerning watching the series. Next, around time point 20 the control states $\mathbf{CO}_{A,B,Y}$ for observation (the grey line) get close to 1, triggered in a similar way (but just a bit slower) as the control states for communication. This gives the relevant observation channel $\mathbf{S}_{A,Y} \rightarrow \mathbf{RS}_{A,B,Y}$ a weight close to 1. Due to that, mutual observation takes place.

Because of these communication and observation actions, the mutual subjective representations $\mathbf{RS}_{M,J,Y}$ of Jenny about Mark (the dark green line) and $\mathbf{RS}_{J,M,Y}$ of Mark about Jenny (the light green line) are formed and around time 20 reach levels around 0.8 (Jenny representing Mark) and 0.9 (Mark representing Jenny), respectively; these representations are close to the actual values, as are the representations $\mathbf{RS}_{A,A}$ of their own states, so all of them achieve faithful representations. Only now these subjective representations have been formed in a controlled manner, the homophily principle can start to work: the bonding works through the (subjective) representation states $\mathbf{RS}_{A,B,Y}$, not through the (objective) states $\mathbf{S}_{A,Y}$ themselves. More specifically, from the moment on that the subjective representations of Jenny about Mark and Jenny's own subjective representation about herself get closer than 0.25, (which is somewhere before time point 10 but not earlier), her self-model representation $\mathbf{RW}_{J,M,Y}$ of her connection to Mark (the pink line) starts to increase from 0.2 or lower to finally becoming very close to 1. Similarly, the effect of the subjective representations of Mark for Jenny and Mark's own subjective self-model representation about himself, on the subsequent increase of his representation $\mathbf{RW}_{M,J,Y}$ of his connection to Jenny (the blue line) can be noted. Before that point in time their connections were not increasing, but instead go slightly downward; this illustrates the effect of the control via the subjective self-model representation states on the adaptation.

13.5 A Social Network Model for Bonding Based on Faking

Next, another example of controlled social network adaptation is addressed. This example concerns how bonding can take place based on faked homophily. Like above, this self-modeling network model integrates three types of interacting processes, modeled at three different levels:

- The considered social base network itself with its (within-network) dynamics for social contagion (Levy and Nail 1993)
- Change of this social network over time based on bonding by homophily (McPherson et al. 2001; Pearson et al. 2006): first-order social network adaptation
- Control of the first-order social network adaptation: second-order social network adaptation

As above, the bonding is not assumed to depend on the objective states for the two persons, but on how these states are perceived and represented by the persons through the formation of subjective state representation states. By controlling the formation of these subjective state representation states, indirectly the bonding is affected; contrarily, if you don't take care to acquire information about the other person, then you miss a good reason for stronger or weaker bonding. To cover this, the above three types of processes have been modeled by a second-order self-modeling network using a first-order self-model (for formation of the subjective state representation states and for the bonding based on them) and a second-order self-model (for the control of the formation of the subjective representation states). This offers some room to model cheating about one's own properties, as regularly happens in real life: by faking an own state, the other person will make a false representation for it, which then will affect that person's bonding in a false manner.

The model's connectivity is depicted in Fig. 13.5 by an example for two persons, one of which is faking his or her properties in order to achieve successful bonding. In this 3D picture, each of the three planes models one of the three types of processes mentioned above; for an explanation of the states, see Table 13.3.

The types of connections used at and between the three levels within this network model are shown in Table 13.2. Here Z is a type of state of a person, for example, how often the person listens to a certain type of music; to keep the notations simple, this type is left out of them; if needed, the Z could be used as an additional subscript.

At the base level, social contagion is modelled by intra-level connections (depicted by black arrows in the lower plane in Fig. 13.5) such as $S_A \rightarrow S_B$, $FS_B \rightarrow S_A$, and $S_A \rightarrow FS_B$. Here the last connection models B faking by intentionally listening to the same type of music as A just at the moments that A can observe it. In contrast to FS_B , state S_B indicates how much B normally listens to that type of music. In the simulated scenario, S_A will have high values and S_B low values, whereas by copying S_A also FS_B gets high values.

Within the first-order self-model, each person has subjective internal representation states of other persons' states Z and the of state Z of her or himself, and also of his or her connections to others. This first-order self-model is modeled in the middle

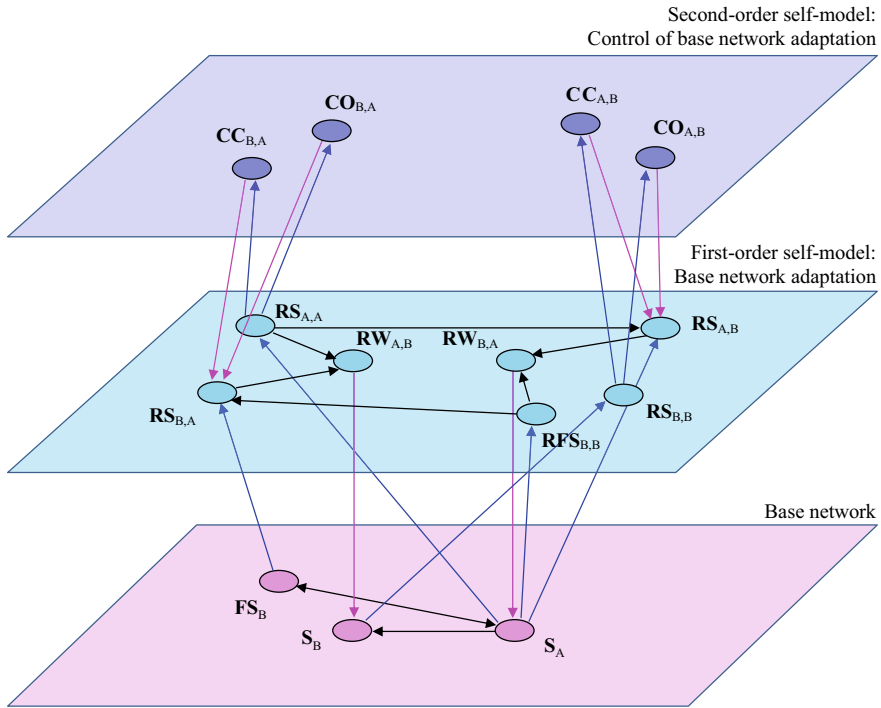


Fig. 13.5 Overview of the connectivity of the second-order adaptive social network model for bonding by homophily for two persons A and B, where B is faking the homophily for A

Table 13.3 Types of states in the introduced controlled adaptive social network model

S_A	Objective state Z of person A
S_B	Objective state Z of person B
FS_B	Objective state of person B faking state Z of person A
$RS_{A,A}$	Subjective representation of person A for state Z of person A
$RS_{B,B}$	Subjective representation of person B for state Z of person B
$RS_{A,B}$	Subjective representation of person B for state Z of person A
$RS_{B,A}$	Subjective representation of person A for state Z of person B
$RFS_{B,B}$	Subjective representation of person B for his or her faked state Z
$RW_{A,B}$	Subjective representation of person A for the weight of the connection from person A to person B
$RW_{B,A}$	Subjective representation of person B for the weight of the connection from person B to person A
$CC_{A,B}$	Control state for communication from A to B for the state Z of A: representation of the weight of the connection from $RS_{A,A}$ to $RS_{A,B}$
$CC_{B,A}$	Control state for communication from B to A for the state Z of B: representation of the weight of the connection from $RS_{B,B}$ to $RS_{B,A}$
$CO_{A,B}$	Control state for observation by B for the state Z of A observed by B: representation of the weight of the connection from S_A to $RS_{A,B}$
$CO_{B,A}$	Control state for observation by A for the state Z of B observed by A: representation of the weight of the connection from S_B to $RS_{B,A}$

plane. For example, person A's internal representation state for person B having state Z is modeled by state representation $\mathbf{RS}_{B,A}$, and A's subjective representation of his or her connection to B is modeled by connection weight representation $\mathbf{RW}_{A,B}$.

There are two pathways that contribute to formation of state representations such as $\mathbf{RS}_{A,B}$. First, these representations can be obtained through observation of \mathbf{S}_A by B. This is modeled by an upward interlevel connection $\mathbf{S}_A \rightarrow \mathbf{RS}_{A,B}$ from the base network to the first-order self-model. As B is faking his or her base state, observation by A is modeled *not* by a connection $\mathbf{S}_B \rightarrow \mathbf{RS}_{B,A}$ but by connection $\mathbf{FS}_B \rightarrow \mathbf{RS}_{B,A}$.

A second pathway for a person B to get information on person A's state is through communication between persons. For example, if A communicates his or her subjective representation $\mathbf{RS}_{A,A}$ of the own state \mathbf{S}_A to B (e.g., 'I often play this type of music!'), this is modeled by an intra-level connection $\mathbf{RS}_{A,A} \rightarrow \mathbf{RS}_{A,B}$ within the middle plane for the first-order self-model. Also in the communication, B is faking; therefore communication from B to A is *not* modeled by a connection $\mathbf{RS}_{A,B} \rightarrow \mathbf{RS}_{B,A}$, but by connection $\mathbf{RFS}_{B,B} \rightarrow \mathbf{RS}_{B,A}$ (so that B may falsely communicate 'What a coincidence, I also often play that type of music!') Table 13.4.

As indicated, person A's representation of her or his connection to person B is modeled by $\mathbf{RW}_{A,B}$. It is assumed that for the bonding by homophily adaptation principle, the adaptive change of the represented connection for A to B depends on the internal representation states $\mathbf{RS}_{B,A}$ and $\mathbf{RS}_{A,A}$. Therefore, this adaptation is supported by intra-level connections $\mathbf{RS}_{A,A} \rightarrow \mathbf{RW}_{A,B}$ and $\mathbf{RS}_{B,A} \rightarrow \mathbf{RW}_{A,B}$ within the first-order self-model. The connection representations by \mathbf{RW} -states in turn affect the social contagion within the social network, which is modeled by downward interlevel connections $\mathbf{RW}_{A,B} \rightarrow \mathbf{S}_B$ and $\mathbf{RW}_{B,A} \rightarrow \mathbf{S}_A$ from the first-order self-model in the middle plane to the base network.

To control the social network adaptation processes, two types of control actions are considered in particular:

- controlling the observation of state Z from person A by person B is modeled by control state $\mathbf{CO}_{A,B}$ and from person B by person A is modeled by control state $\mathbf{CO}_{B,A}$
- controlling the communication about state Z from person A to person B, modeled by control state $\mathbf{CC}_{A,B}$ and the communication about state Z from person B to person A, is modeled by control state $\mathbf{CC}_{B,A}$.

Activation of a communication control state makes that the related connection in the first-order self-model in the middle plane gets a high value (1 or close to 1); this is achieved by interlevel connections from control states to \mathbf{RS} -states in the first-order self-model. For example, activation of communication control state $\mathbf{CC}_{A,B}$ makes that the connection $\mathbf{RS}_{A,A} \rightarrow \mathbf{RS}_{A,B}$ from A's state $\mathbf{RS}_{A,A}$ to B's state $\mathbf{RS}_{A,B}$ gets a high value (1 or close to 1) so that the transfer of information by communication happens; this is modeled by interlevel connection $\mathbf{CO}_{A,B} \rightarrow \mathbf{RS}_{A,B}$. This can be considered as B asking A for the information about him or herself, upon which A communicates

Table 13.4 Connections in the controlled adaptive social network model and their explanation

Intralevel connections		
$S_A \rightarrow S_B$	Social contagion from A to B for state Z	
$FS_B \rightarrow S_A$	Social contagion from B's faked state for Z to A	
$S_A \rightarrow FS_B$	Faking contagion from state Z of A to faked state Z of B	
$RS_{A,A} \rightarrow RS_{A,B}$	Communication of state Z from A to B	
$RFS_{B,B} \rightarrow RS_{B,A}$	Communication of faked state Z from B to A	
$RS_{A,A} \rightarrow RW_{A,B}$	Effect of represented state Z of A by A on the connection from A to B (bonding by homophily)	
$RS_{B,A} \rightarrow RW_{A,B}$	Effect of represented state Z of B by A on the connection from A to B (bonding by homophily)	
$RFS_{B,B} \rightarrow RW_{B,A}$	Effect of represented faked state Z of B by B on the connection from B to A (bonding by homophily)	
$RS_{A,B} \rightarrow RW_{B,A}$	Effect of represented state Z of A by B on the connection from B to A (bonding by homophily)	
Interlevel connections		
$S_A \rightarrow RS_{A,A}$	Impact of observation of A's state Z by A on A's representation of A's state Z	Upward from base network to first-order self-model
$S_B \rightarrow RS_{B,B}$	Impact of observation of B's state Z by B on B's representation of B's state Z	
$S_A \rightarrow RS_{A,B}$	Impact of observation of A's state Z by B on B's representation of A's state Z	
$FS_B \rightarrow RS_{B,A}$	Impact of observation of B's faked state Z by A on A's representation of B's state Z	
$RW_{A,B} \rightarrow S_B$	Effectuation of base connection weight for social contagion from state Z of A to state Z of B	Downward from first-order self-model to base network
$RW_{B,A} \rightarrow S_A$	Effectuation of base connection weight for social contagion from faked state Z of B to state Z of A	
$RS_{A,A} \rightarrow CC_{B,A}$	Communication control monitoring connection for A	Upward from first-order self-model to second-order self-model
$RS_{B,B} \rightarrow CC_{A,B}$	Communication control monitoring connection for B	
$RS_{A,A} \rightarrow CO_{B,A}$	Observation control monitoring connection for A	
$RS_{B,B} \rightarrow CO_{A,B}$	Observation control monitoring connection for B	
$CC_{B,A} \rightarrow RS_{B,A}$	Effectuation of control of communication from B by A	Downward from second-order self-model to first-order self-model

(continued)

Table 13.4 (continued)

$CC_{A,B} \rightarrow RS_{A,B}$	Effectuation of control of communication from A by B
$CO_{B,A} \rightarrow RS_{B,A}$	Effectuation of control of observation of B by A
$CO_{A,B} \rightarrow RS_{A,B}$	Effectuation of control of observation of A by B

this information. Similarly, activation of an observation control state $CO_{A,B}$ makes that the connection $S_A \rightarrow RS_{A,B}$ from A's state S_A to B's state $RS_{A,B}$ gets a high value (1 or close to 1) so that the transfer of information by observation takes place; this is modeled by connection $CO_{A,B} \rightarrow RS_{A,B}$. In the case modeled here, control states such as $CC_{A,B}$ and $CO_{A,B}$ themselves may become active depending on B's state $RS_{B,B}$; this is modeled by connections $RS_{B,B} \rightarrow CC_{A,B}$ and $RS_{B,B} \rightarrow CO_{A,B}$. But this may be addressed in many other ways as well, including externally determined control, for example, by enabling or allowing observation or communication (only) at specific time slots.

To specify a network model according to the approach described in Casciaro et al. (1999), as discussed in Sect. 13.2, three types of network characteristics are to be covered: *connectivity*, *aggregation* and *timing* characteristics. Any state in the network is causally affected by all of such characteristics, each from its own specific role. Following the role matrices specification format defined in Treur (2020b) (pp. 39–41, 89), they are specified by role matrices as shown in Box 1 which are used as input for the dedicated software environment to automatically obtain the simulation discussed In Sect. 13.4.

More specifically, *role matrices* indicate in rows successively for all network states, the factors that causally affect them from the different roles. So in the row for a state Y , in each column a causal relation is specified affecting state Y for the role described by that role matrix. In this way, role matrices describe the network model by mathematical relations and functions.

In the first place, concerning *connectivity* roles, each state is causally affected by the other states from which it has incoming connections and by the weights of these connections. In role matrix **mb** (see Fig. 13.6), for each state it is indicated from which other states it has incoming connections from the same or a lower level. In role matrix **mcw**, it is indicated what are the connection weights for the connected states indicated in **mb**. If these weights are static, their value is indicated, in green shaded cells (here always 1), but if the connection weight is adaptive, instead of a number the self-model state representing this weight is indicated in role matrix **mcw**. This can be seen (cells shaded in a peach-red colour) in **mcw** for the incoming connections for the first two states X_1 and X_2 , and for the incoming connections for the states X_7 and X_8 . Indicating these adaptive value representations, defines the downward

mb base connectivity				mew connection weights				ms speed factors				
		1	2	3			1	2	3			
X_1	S_A	X_3			X_1	S_A	X_{10}			X_1	S_A	0.0005
X_2	S_B	X_1			X_2	S_B	X_9			X_2	S_B	0.0005
X_3	FS_B	X_1			X_3	FS_B	1			X_3	FS_B	0.8
X_4	$RS_{A,A}$	X_1			X_4	$RS_{A,A}$	1			X_4	$RS_{A,A}$	0.9
X_5	$RS_{B,B}$	X_2			X_5	$RS_{B,B}$	1			X_5	$RS_{B,B}$	0.9
X_6	$RFS_{B,B}$	X_1			X_6	$RFS_{B,B}$	1			X_6	$RFS_{B,B}$	0.9
X_7	$RS_{A,B}$	X_1	X_4		X_7	$RS_{A,B}$	X_{13}	X_{11}		X_7	$RS_{A,B}$	0.9
X_8	$RS_{B,A}$	X_3	X_6		X_8	$RS_{B,A}$	X_{14}	X_{12}		X_8	$RS_{B,A}$	0.9
X_9	$RW_{A,B}$	X_4	X_8	X_9	X_9	$RW_{A,B}$	1	1	1	X_9	$RW_{A,B}$	0.1
X_{10}	$RW_{B,A}$	X_6	X_7	X_{10}	X_{10}	$RW_{B,A}$	1	1	1	X_{10}	$RW_{B,A}$	0.1
X_{11}	$CC_{A,B}$	X_4			X_{11}	$CC_{A,B}$	1			X_{11}	$CC_{A,B}$	0.2
X_{12}	$CC_{B,A}$	X_3			X_{12}	$CC_{B,A}$	1			X_{12}	$CC_{B,A}$	0.2
X_{13}	$CO_{A,B}$	X_4			X_{13}	$CO_{A,B}$	1			X_{13}	$CO_{A,B}$	0.4
X_{14}	$CO_{B,A}$	X_3			X_{14}	$CO_{B,A}$	1			X_{14}	$CO_{B,A}$	0.4

mcfw combination function weights				mcfp combination function parameters				iv initial values						
		1	2	3			1	2	3			1		
		eucl	slhomo	alogistic			hom	log						
X_1	S_A	1			X_1	S_A	1	1				X_1	S_A	0.9
X_2	S_B	1			X_2	S_B	1	1				X_2	S_B	0.2
X_3	FS_B	1			X_3	FS_B	1	1				X_3	FS_B	0.2
X_4	$RS_{A,A}$	1			X_4	$RS_{A,A}$	1	1				X_4	$RS_{A,A}$	0.7
X_5	$RS_{B,B}$	1			X_5	$RS_{B,B}$	1	1				X_5	$RS_{B,B}$	0.4
X_6	$RFS_{B,B}$	1			X_6	$RFS_{B,B}$	1	1				X_6	$RFS_{B,B}$	0.5
X_7	$RS_{A,B}$	1			X_7	$RS_{A,B}$	1	2				X_7	$RS_{A,B}$	0.5
X_8	$RS_{B,A}$	1			X_8	$RS_{B,A}$	1	2				X_8	$RS_{B,A}$	0.5
X_9	$RW_{A,B}$		1		X_9	$RW_{A,B}$		3	0.25			X_9	$RW_{A,B}$	0.5
X_{10}	$RW_{B,A}$		1		X_{10}	$RW_{B,A}$		3	0.25			X_{10}	$RW_{B,A}$	0.5
X_{11}	$CC_{A,B}$			1	X_{11}	$CC_{A,B}$			50	0.1		X_{11}	$CC_{A,B}$	0
X_{12}	$CC_{B,A}$			1	X_{12}	$CC_{B,A}$			50	0.1		X_{12}	$CC_{B,A}$	0
X_{13}	$CO_{A,B}$			1	X_{13}	$CO_{A,B}$			50	0.1		X_{13}	$CO_{A,B}$	0
X_{14}	$CO_{B,A}$			1	X_{14}	$CO_{B,A}$			50	0.1		X_{14}	$CO_{B,A}$	0

Fig. 13.6 Full specification of the adaptive self-modeling network model by role matrices for all (connectivity, aggregation and timing) characteristics causally affecting the network states

connections of Fig. 13.1. From the *timing role*, also its speed factor causally affects a state; they are shown in Fig. 13.6 (role matrix **ms**, which actually is a vector).

In the lower part of Fig. 13.6, showing the *aggregation* roles causally affecting a state, it can be seen which states use which combination functions (role matrix **mcfw**) and which parameter values for them (role matrix **mcfp**). In addition to the five role matrices for the different roles of causal impacts, the initial values for the example simulation are also shown in Fig. 13.6, which may be considered as initial causal impacts.

13.6 Simulation: Faking Homophily for Bonding

In this section, a simulation of a simulated example scenario will be discussed to illustrate the introduced second-order adaptive causal social network model for faking homophily. In Fig. 13.7 the simulation for the example scenario is shown. Here the

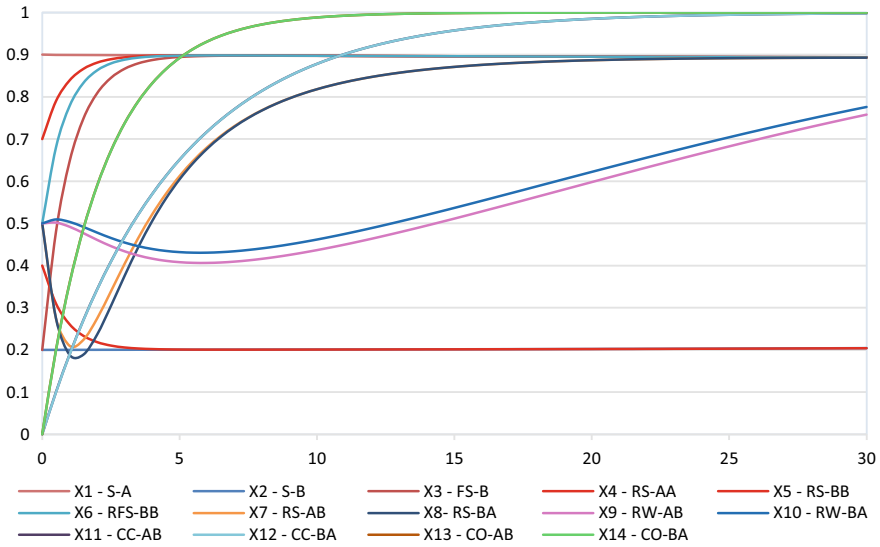


Fig. 13.7 Outcomes for the example scenario simulation

states S_X are slowly changing whereas the connection representations in the form of the **RW**-states are changing faster. It indeed can be seen that for A and B both directional connection representations $RW_{A,B}$ and $RW_{B,A}$ start to gradually increase from time point 5 on to reach values above 0.7 which in the long run eventually reach a value (close to) 1. These changes of the connections are a consequence of the homophily principle, as the values of state S_A of A and the faked states FS_B and $RFS_{B,B}$ for B quickly get close to each other; note that the tipping point for similarity set was 0.25, so a difference between the relevant representation states < 0.25 is strengthening a connection.

In Fig. 13.7, also the roles that are played by the control states in the form of the **CO**- and **CC**-states and by the **RS**-states for subjective representations can be seen. The two lines that start at 0 and get close to 1 around or soon after time 10 indicate the control states $CO_{A,B}$ and $CO_{B,A}$ (light green) for observation and $CC_{A,B}$ and $CC_{B,A}$ (light blue) for communication, respectively. This makes that at that time their mutual observation and communication channels $S_A \rightarrow RS_{A,B}$ and $FS_B \rightarrow RS_{B,A}$, and $RS_{A,A} \rightarrow RS_{A,B}$ and $RFS_{B,B} \rightarrow RS_{B,A}$ get weights close to 1. This implies that then they indeed both observe and communicate to each other about the type of music they usually listen to. These control states are triggered in this example scenario because each of the persons automatically observes his or herself and therefore they quickly (before time point 4) form representation states $RS_{A,A}$ and $RS_{B,B}$ of their own **S**-states concerning music (the red lines, starting at 0.4 for B and at 0.7 for A).

Because of these communication and observation actions, the mutual subjective representations $RS_{A,B}$ of B about A (the dark green line) and $RS_{B,A}$ of A about B

(the orange line) based on fake information are formed, and around time 20 reach levels close to 0.9. Only now these subjective representations have been formed in a controlled manner, the homophily principle can start to work, as the bonding works through the (subjective) representation **RS**-states, not through the (objective) states **S_X** themselves. More specifically, from the moment on that the subjective representations of A about B and A's own subjective representation about her- or himself get closer than 0.25 (which is just before time point 5), her/his self-model representation **RW_{A,B}** of her connection to B (the pink line) starts to gradually increase. Similarly, the effect of the subjective representations of B for A and B's own subjective self-model representation about him or herself, on the subsequent increase of his representation **RW_{B,A}** of this connection to A (the blue line) can be noted. Before that point in time their connections were not increasing, but instead go slightly downward; this illustrates the effect of the control via the subjective self-model representation states on the adaptation.

13.7 Discussion

In this chapter, a computational analysis was made of the role of subjective elements and control in social network adaptation. Part of the content is based on (Treur 2021). It was analysed: (1) how the coevolution of social contagion and bonding by homophily may be controlled by the persons involved, and (2) how subjective representation states (e.g., what they know about themselves and each other and about their connections) can play a role in this coevolution and its control. To address this, a second-order adaptive social network model was presented in which persons do have a form of control over the coevolution process, and, in relation to this, their bonding depends on their subjective representation states about themselves and about each other, and social contagion depends on their subjective representation states about their connections.

Concerning evaluation, the model behaviour is as expected from the mentioned literature. Moreover, based on mathematical analysis, from Formula (13.3) for the homophily function it can be predicted that when the model reaches an equilibrium, it holds:

$$W = 0 \text{ or } W = 1 \text{ or } |V_1 - V_2| = \tau_{\text{homo}}$$

This is indeed the case, as can also be seen in the case study simulation in Fig. 13.3 where all connection weight representations end up in 0 or 1.

Also note that a basic design choice for the model is that the subjective representations of the connections determine the actual social contagion in the objective social world. This is based on the assumption that persons socially behave according to what they know or believe about their connections. Also here misrepresentation can be modeled easily by introducing some deviations in the subjective bonding by homophily mechanism within the model. Then the social behaviour leading to social

contagion will (falsely) take place based on these misrepresentations of connections. On the other hand, it may as well be assumed that the subjective representations of the connections do not play an exclusive role in the social behaviour, but also a more objective form of connections may have influence. To cover this, the model can easily be extended by also adding (in parallel) a more standard objective mechanism for bonding by homophily based on the objective states and then combine (according to some chosen ratio) both the objective and subjective connection representations to jointly make social contagion work. Also this may be worked out in more detail for a possible extended version for a journal.

The proposed computational network model where mental states are modeled as a basis for social mechanisms also roughly relates to (noncomputational) literature in Social Science such as (Casciaro et al. 1999; Krackhardt 1987; Vaisey and Lizardo 2010) which addresses more in general the role of cognitive interpretation and cultural influence on social interactions. Such literature may provide inspiration to design computational network models for other situations where mental states and social dynamics interact.

Adaptation inhibition of social networks (e.g., for terrorists), is a topic addressed in Carley (2002, 2006). It can be an interesting challenge to explore in how far a similar architecture for controlling social network adaptation as discussed in the current chapter can be applied to these types of inhibited adaptive social networks. Other possible extensions may consider the integration of different adaptation principles, such as addressed (without control), for example, in Beukel et al. (2019).

13.8 Specification of the Main Adaptive Network Model

First box: Role matrices **mb** and **mcw** for the connectivity and **ms** for timing characteristics of the network model. Fig. 13.9

Second box: Role matrices **mcfw** and **mcfp** for the aggregation characteristics and the initial values of the network model. Fig. 13.8, 13.9.

mb				mcw				ms				
base connectivity		1	2	3	connection weights		1	2	3	speed factors		1
X_1	S_M	X_2	X_3	X_4	X_1	S_M	X_{27}	X_{28}	X_{29}	X_1	S_M	0.0005
X_2	S_D	X_1	X_3	X_4	X_2	S_D	X_{21}	X_{30}	X_{31}	X_2	S_D	0.0005
X_3	S_J	X_1	X_2	X_4	X_3	S_J	X_{22}	X_{24}	X_{32}	X_3	S_J	0.0005
X_4	S_A	X_1	X_2	X_3	X_4	S_A	X_{23}	X_{25}	X_{26}	X_4	S_A	0.0005
X_5	$RS_{M,M}$	X_1			X_5	$RS_{M,M}$	1			X_5	$RS_{M,M}$	0.9
X_6	$RS_{D,D}$	X_2			X_6	$RS_{D,D}$	1			X_6	$RS_{D,D}$	0.9
X_7	$RS_{J,J}$	X_3			X_7	$RS_{J,J}$	1			X_7	$RS_{J,J}$	0.9
X_8	$RS_{A,A}$	X_4			X_8	$RS_{A,A}$	1			X_8	$RS_{A,A}$	0.9
X_9	$RS_{M,D}$	X_1	X_5		X_9	$RS_{M,D}$	X_{45}	X_{33}		X_9	$RS_{M,D}$	0.9
X_{10}	$RS_{M,J}$	X_1	X_5		X_{10}	$RS_{M,J}$	X_{46}	X_{34}		X_{10}	$RS_{M,J}$	0.9
X_{11}	$RS_{M,A}$	X_1	X_5		X_{11}	$RS_{M,A}$	X_{47}	X_{35}		X_{11}	$RS_{M,A}$	0.9
X_{12}	$RS_{D,J}$	X_2	X_6		X_{12}	$RS_{D,J}$	X_{48}	X_{36}		X_{12}	$RS_{D,J}$	0.9
X_{13}	$RS_{D,A}$	X_2	X_6		X_{13}	$RS_{D,A}$	X_{49}	X_{37}		X_{13}	$RS_{D,A}$	0.9
X_{14}	$RS_{J,A}$	X_3	X_7		X_{14}	$RS_{J,A}$	X_{50}	X_{38}		X_{14}	$RS_{J,A}$	0.9
X_{15}	$RS_{D,M}$	X_2	X_6		X_{15}	$RS_{D,M}$	X_{51}	X_{39}		X_{15}	$RS_{D,M}$	0.9
X_{16}	$RS_{J,M}$	X_3	X_7		X_{16}	$RS_{J,M}$	X_{52}	X_{40}		X_{16}	$RS_{J,M}$	0.9
X_{17}	$RS_{A,M}$	X_4	X_8		X_{17}	$RS_{A,M}$	X_{53}	X_{41}		X_{17}	$RS_{A,M}$	0.9
X_{18}	$RS_{J,D}$	X_3	X_7		X_{18}	$RS_{J,D}$	X_{54}	X_{42}		X_{18}	$RS_{J,D}$	0.9
X_{19}	$RS_{A,D}$	X_4	X_8		X_{19}	$RS_{A,D}$	X_{55}	X_{43}		X_{19}	$RS_{A,D}$	0.9
X_{20}	$RS_{A,J}$	X_4	X_8		X_{20}	$RS_{A,J}$	X_{56}	X_{44}		X_{20}	$RS_{A,J}$	0.9
X_{21}	$RW_{M,D}$	X_5	X_{15}	X_{21}	X_{21}	$RW_{M,D}$	1	1	1	X_{21}	$RW_{M,D}$	0.1
X_{22}	$RW_{M,J}$	X_5	X_{16}	X_{22}	X_{22}	$RW_{M,J}$	1	1	1	X_{22}	$RW_{M,J}$	0.1
X_{23}	$RW_{M,A}$	X_5	X_{17}	X_{23}	X_{23}	$RW_{M,A}$	1	1	1	X_{23}	$RW_{M,A}$	0.1
X_{24}	$RW_{D,J}$	X_6	X_{18}	X_{24}	X_{24}	$RW_{D,J}$	1	1	1	X_{24}	$RW_{D,J}$	0.1
X_{25}	$RW_{D,A}$	X_6	X_{19}	X_{25}	X_{25}	$RW_{D,A}$	1	1	1	X_{25}	$RW_{D,A}$	0.1
X_{26}	$RW_{J,A}$	X_7	X_{20}	X_{26}	X_{26}	$RW_{J,A}$	1	1	1	X_{26}	$RW_{J,A}$	0.1
X_{27}	$RW_{D,M}$	X_6	X_9	X_{27}	X_{27}	$RW_{D,M}$	1	1	1	X_{27}	$RW_{D,M}$	0.1
X_{28}	$RW_{J,M}$	X_7	X_{10}	X_{28}	X_{28}	$RW_{J,M}$	1	1	1	X_{28}	$RW_{J,M}$	0.1
X_{29}	$RW_{A,M}$	X_8	X_{11}	X_{29}	X_{29}	$RW_{A,M}$	1	1	1	X_{29}	$RW_{A,M}$	0.1
X_{30}	$RW_{J,D}$	X_7	X_{12}	X_{30}	X_{30}	$RW_{J,D}$	1	1	1	X_{30}	$RW_{J,D}$	0.1
X_{31}	$RW_{A,D}$	X_8	X_{13}	X_{31}	X_{31}	$RW_{A,D}$	1	1	1	X_{31}	$RW_{A,D}$	0.1
X_{32}	$RW_{A,J}$	X_8	X_{14}	X_{32}	X_{32}	$RW_{A,J}$	1	1	1	X_{32}	$RW_{A,J}$	0.1
X_{33}	$CC_{M,D}$	X_6			X_{33}	$CC_{M,D}$	1			X_{33}	$CC_{M,D}$	0.2
X_{34}	$CC_{M,J}$	X_7			X_{34}	$CC_{M,J}$	1			X_{34}	$CC_{M,J}$	0.2
X_{35}	$CC_{M,A}$	X_8			X_{35}	$CC_{M,A}$	1			X_{35}	$CC_{M,A}$	0.2
X_{36}	$CC_{D,J}$	X_7			X_{36}	$CC_{D,J}$	1			X_{36}	$CC_{D,J}$	0.2
X_{37}	$CC_{D,A}$	X_8			X_{37}	$CC_{D,A}$	1			X_{37}	$CC_{D,A}$	0.2
X_{38}	$CC_{J,A}$	X_8			X_{38}	$CC_{J,A}$	1			X_{38}	$CC_{J,A}$	0.2
X_{39}	$CC_{D,M}$	X_5			X_{39}	$CC_{D,M}$	1			X_{39}	$CC_{D,M}$	0.2
X_{40}	$CC_{J,M}$	X_5			X_{40}	$CC_{J,M}$	1			X_{40}	$CC_{J,M}$	0.2
X_{41}	$CC_{A,M}$	X_5			X_{41}	$CC_{A,M}$	1			X_{41}	$CC_{A,M}$	0.2
X_{42}	$CC_{J,D}$	X_6			X_{42}	$CC_{J,D}$	1			X_{42}	$CC_{J,D}$	0.2
X_{43}	$CC_{A,D}$	X_6			X_{43}	$CC_{A,D}$	1			X_{43}	$CC_{A,D}$	0.2
X_{44}	$CC_{A,J}$	X_7			X_{44}	$CC_{A,J}$	1			X_{44}	$CC_{A,J}$	0.2
X_{45}	$CO_{M,D}$	X_6			X_{45}	$CO_{M,D}$	1			X_{45}	$CO_{M,D}$	0.4
X_{46}	$CO_{M,J}$	X_7			X_{46}	$CO_{M,J}$	1			X_{46}	$CO_{M,J}$	0.4
X_{47}	$CO_{M,A}$	X_8			X_{47}	$CO_{M,A}$	1			X_{47}	$CO_{M,A}$	0.4
X_{48}	$CO_{D,J}$	X_7			X_{48}	$CO_{D,J}$	1			X_{48}	$CO_{D,J}$	0.4
X_{49}	$CO_{D,A}$	X_8			X_{49}	$CO_{D,A}$	1			X_{49}	$CO_{D,A}$	0.4
X_{50}	$CO_{J,A}$	X_8			X_{50}	$CO_{J,A}$	1			X_{50}	$CO_{J,A}$	0.4
X_{51}	$CO_{D,M}$	X_5			X_{51}	$CO_{D,M}$	1			X_{51}	$CO_{D,M}$	0.4
X_{52}	$CO_{J,M}$	X_5			X_{52}	$CO_{J,M}$	1			X_{52}	$CO_{J,M}$	0.4
X_{53}	$CO_{A,M}$	X_5			X_{53}	$CO_{A,M}$	1			X_{53}	$CO_{A,M}$	0.4
X_{54}	$CO_{J,D}$	X_6			X_{54}	$CO_{J,D}$	1			X_{54}	$CO_{J,D}$	0.4
X_{55}	$CO_{A,D}$	X_6			X_{55}	$CO_{A,D}$	1			X_{55}	$CO_{A,D}$	0.4
X_{56}	$CO_{A,J}$	X_7			X_{56}	$CO_{A,J}$	1			X_{56}	$CO_{A,J}$	0.4

Fig. 13.8 Role matrices mb, mcw and ms for the first example

mcfw	combi- nation function weights	1			2			3			iv	initial	
		eucl	slhomo	3	eucl	slhomo	3	aloga- stic		S _M		S _D	S _J
								1	2				
X_1	S _M	1										0.8	
X_2	S _D	1										0.3	
X_3	S _J	1										0.9	
X_4	S _A	1										0.2	
X_5	RS _{M,M}	1										0.8	
X_6	RS _{D,D}	1										0.3	
X_7	RS _{J,J}	1										0.9	
X_8	RS _{A,A}	1										0.2	
X_9	RS _{M,D}	1										0.5	
X_{10}	RS _{M,J}	1										0.5	
X_{11}	RS _{M,A}	1										0.5	
X_{12}	RS _{D,J}	1										0.5	
X_{13}	RS _{D,A}	1										0.5	
X_{14}	RS _{J,A}	1										0.5	
X_{15}	RS _{D,M}	1										0.5	
X_{16}	RS _{J,M}	1										0.5	
X_{17}	RS _{A,M}	1										0.5	
X_{18}	RS _{J,D}	1										0.5	
X_{19}	RS _{A,D}	1										0.5	
X_{20}	RS _{A,J}	1										0.5	
X_{21}	RW _{M,D}		1									0.85	
X_{22}	RW _{M,J}		1									0.5	
X_{23}	RW _{M,A}		1									0.25	
X_{24}	RW _{D,J}		1									0.1	
X_{25}	RW _{D,A}		1									0.05	
X_{26}	RW _{J,A}		1									0.15	
X_{27}	RW _{D,M}		1									0.75	
X_{28}	RW _{J,M}		1									0.85	
X_{29}	RW _{A,M}		1									0.25	
X_{30}	RW _{J,D}		1									0.1	
X_{31}	RW _{A,D}		1									0.05	
X_{32}	RW _{A,J}		1									0.15	
X_{33}	CC _{M,D}			1								0	
X_{34}	CC _{M,J}			1					50	0.1		0	
X_{35}	CC _{M,A}			1					50	0.1		0	
X_{36}	CC _{D,J}			1					50	0.1		0	
X_{37}	CC _{D,A}			1					50	0.1		0	
X_{38}	CC _{J,A}			1					50	0.1		0	
X_{39}	CC _{D,M}			1					50	0.1		0	
X_{40}	CC _{J,M}			1					50	0.1		0	
X_{41}	CC _{A,M}			1					50	0.1		0	
X_{42}	CC _{J,D}			1					50	0.1		0	
X_{43}	CC _{A,D}			1					50	0.1		0	
X_{44}	CC _{A,J}			1					50	0.1		0	
X_{45}	CO _{M,D}			1					50	0.1		0	
X_{46}	CO _{M,J}			1					50	0.1		0	
X_{47}	CO _{M,A}			1					50	0.1		0	
X_{48}	CO _{D,J}			1					50	0.1		0	
X_{49}	CO _{D,A}			1					50	0.1		0	
X_{50}	CO _{J,A}			1					50	0.1		0	
X_{51}	CO _{D,M}			1					50	0.1		0	
X_{52}	CO _{J,M}			1					50	0.1		0	
X_{53}	CO _{A,M}			1					50	0.1		0	
X_{54}	CO _{J,D}			1					50	0.1		0	
X_{55}	CO _{A,D}			1					50	0.1		0	
X_{56}	CO _{A,J}			1					50	0.1		0	

Fig. 13.9 Role matrices mcfw, mcfp and the initial values ms for the first example

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