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Controlled Social Network Adaptation: Subjective Elements in an Objective Social World

Jan Treur

Abstract In this paper, the role of subjective elements and control in social network adaptation is analyzed computationally. In particular, it is analyzed: (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

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 the 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., [12, 13]). On the other hand, social contagion makes that network states affect each other through their connections, which implies that the stronger the two persons are connected, the more they will become alike [10]. This makes circular, reciprocal causal relations between the two processes. It has been found in simulations that, as in the real world, the emerging behavior of adaptive network models

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based on the coevolution of these two processes often shows a form of clustering, segregation or community formation (e.g., [3, 4, 8, 14, 16, 17, 20, 21]).

Usually, as mentioned in the literature, these social processes are considered without taking into account subjective elements for the persons involved. For example, do the persons themselves actually know 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 willless 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 social science literature works such as [7, 9, 22] from a wider perspective also the role of cognitive and cultural interpretation in social dynamics is emphasized.

In the current paper, it is assumed that such subjective elements indeed do matter and it is analyzed computationally how some of them can play their role in the coevolution process. More specifically, it is analyzed: (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, others and 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 paper, in Sect. 2 the higher-order adaptive network-oriented modeling approach from [19] used is briefly explained. In Sect. 3 the designed second-order adaptive social network model is presented. Section 4 addresses simulation results for a case study on adaptation in tetradic relationships. Finally, Sect. 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 the desired bonding.

2 Higher-Order Adaptive Network Models

In this section, the network-oriented modeling approach used is briefly introduced. Following [15, 19], a temporal-causal network model is characterized by:

- **Connectivity characteristics** Connections from a state X to a state Y and their weights $\boldsymbol{\omega}_{X,Y}$
- **Aggregation characteristics** For any node Y, some combination function $\mathbf{c}_Y(..)$ defines aggregation that is applied to the impacts $\boldsymbol{\omega}_{X_i,Y} X_i(t)$ on Y from its incoming connections from states $X_1, \ldots, X_k$
- **Timing characteristics** Each state Y has a speed factor $\boldsymbol{\eta}_Y$ defining how fast it changes for the 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 $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\boldsymbol{\eta}_Y$:

$$Y(t+\Delta t) = Y(t) + \eta_Y\left[\mathbf{c}_Y\left(\boldsymbol{\omega}_{X_1,Y}X_1(t),\ \ldots,\ \boldsymbol{\omega}_{X_k,Y}X_k(t)\right) - Y(t)\right]\Delta t \tag{1}$$

for any state Y and where $X_1, \ldots, X_k$ are the states from which it gets its incoming connections. Within the software environment described in [19] (Chap. 9), a large number > 45 of useful combination functions are included in a combination function library. The three combination functions from this library used for state Y in the introduced network model are:

- The Euclidean combination function $\mathbf{eucl}_{n,\lambda}(V_1, \ldots, V_\mathrm{k})$ defined by

$$\mathbf{eucl}_{n,\lambda}(V_1,\ \ldots,\ V_k) = \sqrt[n]{\frac{{V_1}^n + \cdots + {V_k}^n}{\lambda}} \tag{2}$$

where n is the order, $\boldsymbol{\lambda}$ is a scaling factor and $V_1, \ldots, V_k$ are the impacts from which the considered state Y gets incoming connections.

- The advanced logistic sum combination function $\mathbf{alogistic}_{\sigma,\tau_{log}}(V_1, \ldots, V_k)$ defined by:

$$\mathbf{alogistic}_{\sigma,\tau_{\mathrm{log}}}(V_1,\ldots,V_k) = \left[\frac{1}{1+\mathrm{e}^{-\sigma(V_1+\ldots+V_k-\tau_{\mathrm{log}})}} - \frac{1}{1+\mathrm{e}^{\sigma\tau_{\mathrm{log}}}}\right]\left(1+\mathrm{e}^{-\sigma\tau_{\mathrm{log}}}\right) \tag{3}$$

where $\boldsymbol{\sigma}$ is a steepness parameter, $\boldsymbol{\tau}_{\mathbf{log}}$ is a threshold parameter and $V_1, \ldots, V_k$ are the impacts from the states from which the considered state Y gets incoming connections

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

$$\mathbf{slhomo}_{\alpha,\tau_{\mathrm{homo}}}(V_1,\ V_2,\ W) = W + \alpha W(1-W)(\boldsymbol{\tau}_{\mathbf{homo}} - |V_1 - V_2|) \tag{4}$$

where $\boldsymbol{\alpha}$ is an amplification parameter, $\boldsymbol{\tau}_{\mathbf{homo}}$ is 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. 3, the combination function $\mathbf{eucl}_{n,\lambda}(\ldots)$ will be used to model social contagion and formation of internal state representations, $\mathbf{slhomo}_{\alpha,\tau_{\mathrm{homo}}}(V_1,\ V_2,\ W)(V_1, V_2, W)$ to model bonding based on homophily by internal connection weight representations, and $\mathbf{alogistic}_{\sigma,\tau_{\mathrm{log}}}(\ldots)$ to model control of the bonding. Note that the homophily tipping point $\boldsymbol{\tau}_{\mathbf{homo}}$ 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 $> W$) into a decrease (outcome $< W$), 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 conceptualization can also be applied to *adaptive* networks to obtain a declarative description using mathematically defined functions and relations for them as well; see [18, 19]. This works through the addition of new states to the network (called *reification states* or *self-model 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 the next level (*reification level*), where the original network is at a *base level*. As an example, the weight $\boldsymbol{\omega}_{X,Y}$ of a connection from state X to state Y can be represented (at the next reification 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 $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(\ldots)$, $\boldsymbol{\eta}_Y$ 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 [19], Chap. 10, this self-modeling construction can be easily 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 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., [1, 11, 19], Chap. 4). In the current paper, multi-level network self-modeling will be applied for higher-order adaptive social network models in particular.

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. 2, with connectivity as depicted in Fig. 1. In this 3D picture, of the three-plane models, one of the three types of processes is mentioned above.

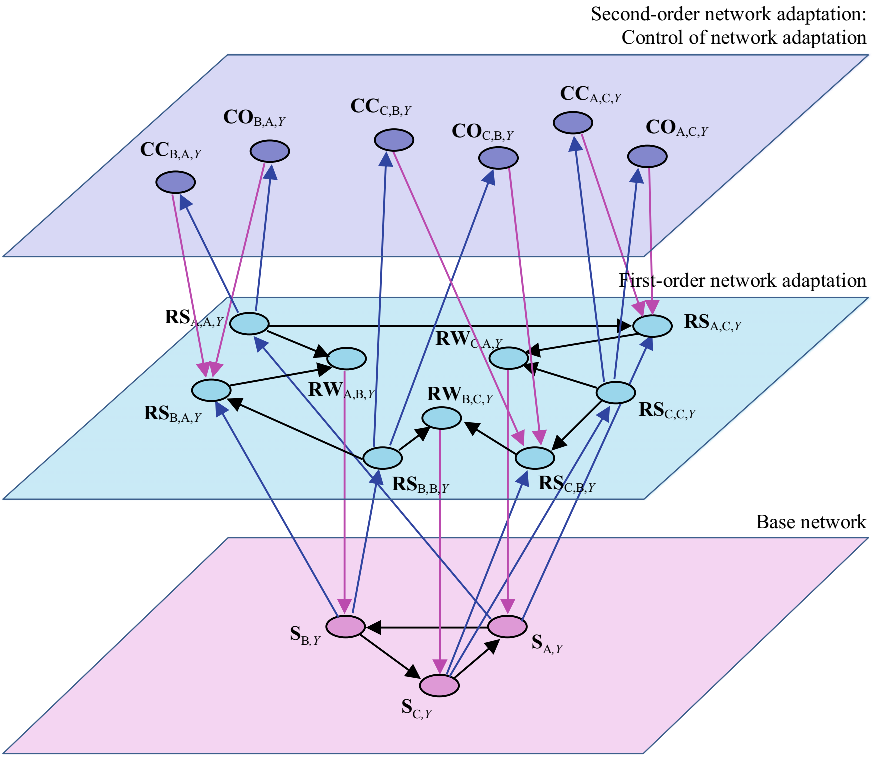

Fig. 1 Overview of the connectivity of the second-order adaptive social network model for three example persons A, B and C

The types of states and connections used at and between the three levels within this network model are shown in Tables 1 and 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 modeled by connections $\mathbf{S}_{A,Y} \rightarrow \mathbf{S}_{B,Y}$. 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

Table 1 Types of states in the introduced controlled adaptive social network model

$\mathbf{S}_{B,Y}$	Objective state Y of person B
$\mathbf{RS}_{A,B,Y}$	Subjective representation of person B for state Y of person A
$\mathbf{RW}_{A,B,Y}$	Subjective representation of person A for the connection weight from person A to person B
$\mathbf{CC}_{A,B,Y}$	Control state for communication from A to B: representation of the weight of the connection from $\mathbf{RS}_{A,A,Y}$ to $\mathbf{RS}_{A,B,Y}$
$\mathbf{CO}_{A,B,Y}$	Control state for observation by B: representation of the weight of the connection from $\mathbf{S}_{A,Y}$ to $\mathbf{RS}_{A,B,Y}$ for the state Y of A observed by B

Table 2 Types of connections in the controlled adaptive social network model

Intralevel connections		
$\mathbf{S}_{A,Y} \to \mathbf{S}_{B,Y}$	Social contagion from A to B for state Y	
$\mathbf{RS}_{A,A,Y} \to \mathbf{RS}_{A,B,Y}$	Communication of $\mathbf{S}_{A,Y}$ from A to B	
$\mathbf{RS}_{A,A,Y} \to \mathbf{RW}_{A,B,Y}$	Effect of state Y of A on bonding by homophily from A to B	
$\mathbf{RS}_{B,A,Y} \to \mathbf{RW}_{A,B,Y}$	Effect of state Y of B on bonding by homophily from A to B	
Interlevel connections		
$\mathbf{S}_{A,Y} \to \mathbf{RS}_{A,B,Y}$	Observation by B of A's state Y	Upward from base level to first reification level
$\mathbf{RW}_{A,B,Y} \to \mathbf{S}_{B,Y}$	Effectuation of base connection weights for social contagion from A to B	Downward from first reification level to base level
$\mathbf{RS}_{B,B,Y} \to \mathbf{CO}_{A,B,Y}$	Observation control monitoring connections for B	Upward from first to second reification level
$\mathbf{RS}_{B,B,Y} \to \mathbf{CC}_{A,B,Y}$	Communication control monitoring connections for B	
$\mathbf{CO}_{A,B,Y} \to \mathbf{RS}_{A,B,Y}$	Effectuation of control of observation of A by B	Downward from second to first reification level
$\mathbf{CC}_{A,B,Y} \to \mathbf{RS}_{A,B,Y}$	Effectuation of control of communication from A by B	

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 $\mathbf{RS}_{A,B,Y}$. A person A's subjective representation of his or her connection to B is modeled by connection weight representation $\mathbf{RW}_{A,B,Y}$. There are two pathways that contribute to the formation of state representations $\mathbf{RS}_{A,B,Y}$. First, these representations can be communicated between persons. For example, if A communicates his or her subjective representation $\mathbf{RS}_{A,A,Y}$ of the own state $\mathbf{S}_{A,Y}$ to B, this is modeled by a connection $\mathbf{RS}_{A,A,Y} \to \mathbf{RS}_{A,B,Y}$. A second pathway for a person B to get information on person A's state is through observation of $\mathbf{S}_{A,Y}$ by B. This is modeled by a connection $\mathbf{S}_{A,Y} \to \mathbf{RS}_{A,B,Y}$.

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

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 $\mathbf{CC}_{A,B,Y}$

- Controlling the observation of state Y from person A by person B, modeled by control states $\mathbf{CO}_{A,B,Y}$

Activation of a communication control state $\mathbf{CC}_{A,B,Y}$ makes that the connection $\mathbf{RS}_{A,A,Y} \rightarrow \mathbf{RS}_{A,B,Y}$ from A's state $\mathbf{RS}_{A,A,Y}$ to B's state $\mathbf{RS}_{A,B,Y}$ gets a high value (1 or close to 1) so that the transfer of information by communication happens; this is modeled by connections $\mathbf{CO}_{A,B,Y} \rightarrow \mathbf{RS}_{A,B,Y}$. 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 $\mathbf{CO}_{A,B,Y}$ makes that the connection $\mathbf{S}_{A,Y} \rightarrow \mathbf{RS}_{A,B,Y}$ from A's state $\mathbf{S}_{A,Y}$ to B's state $\mathbf{RS}_{A,B,Y}$ gets a high value (1 or close to 1) so that the transfer of information by observation takes place; this is modeled by connections $\mathbf{CO}_{A,B,Y} \rightarrow \mathbf{RS}_{A,B,Y}$. As an example used in the case study in Sect. 4, the control states $\mathbf{CC}_{A,B,Y}$ and $\mathbf{CO}_{A,B,Y}$ themselves may become active depending on B's state $\mathbf{RS}_{B,B,Y}$; this is modeled by connections $\mathbf{RS}_{B,B,Y} \rightarrow \mathbf{CO}_{A,B,Y}$ and $\mathbf{RS}_{B,B,Y} \rightarrow \mathbf{CO}_{A,B,Y}$. 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.

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. 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 (instead they have a preference for outdoor activities).

To specify a network model according to the approach described in [19], as discussed in Sect. 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 [23] and used for the simulation discussed

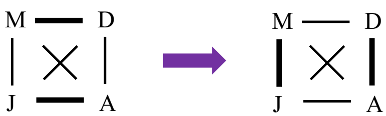

Fig. 2 Example scenario for a tetradic relationship configuration where initially M and D and J and A have strong connections and in the end M and J and D and A have the strong connections

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 Appendix [23]), 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. 1. Also, the speed factors are shown in Appendix [23] (role matrix **ms**, which actually is a vector).

In the second box in Appendix [23], 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. 3 and 4 the simulation for the example scenario is shown. In Fig. 3 the coevolution of changing states and connection (self-model) representations is shown without showing the underlying personal state representations. Here the states $\mathbf{S}_A$ are slowly changing, whereas the connection representations $\mathbf{RW}_{A,B}$ are changing faster. It can be indeed seen that for Mark and Jenny both directional connection representations $\mathbf{RW}_{\mathrm{M,J}}$ and $\mathbf{RW}_{\mathrm{J,M}}$ start to increase from timepoint 5 resp. 10 on to finally end up at a value (close to) 1. Similarly, the connection representations $\mathbf{RW}_{\mathrm{D,A}}$ and $\mathbf{RW}_{\mathrm{A,D}}$ between Dion and Ann start to increase after time 5. In the same time period, the connection representations $\mathbf{RW}_{\mathrm{M,D}}$ and $\mathbf{RW}_{\mathrm{D,M}}$ between Mark and Dion and $\mathbf{RW}_{\mathrm{J,A}}$ and $\mathbf{RW}_{\mathrm{A,J}}$ between Jenny and Ann decrease to (close to) 0. All

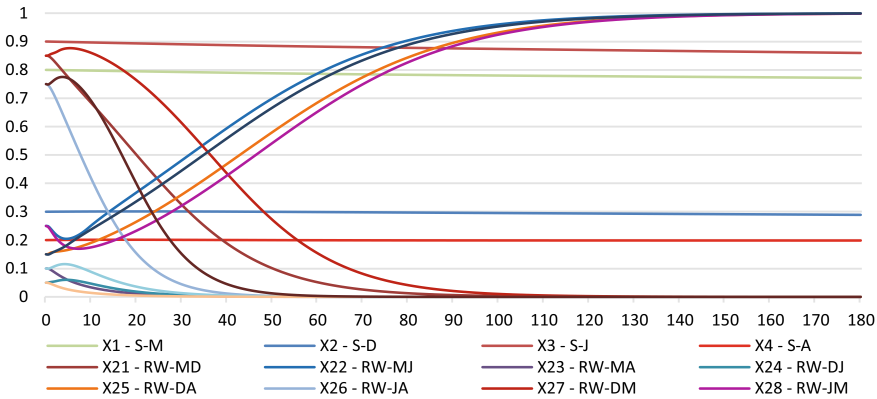

Fig. 3 Outcomes for the example scenario simulation: the changes in all relationships

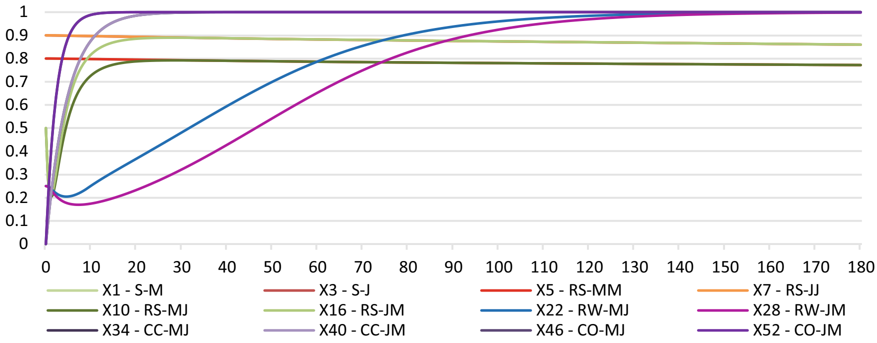

Fig. 4 The role of control and subjective states for the relationship between Mark and Jenny

these changes are a consequence of the homophily principle, as the state values $\mathbf{S}_{\mathrm{M}}$ and $\mathbf{S}_{\mathrm{J}}$ for Mark and Jenny are close to each other (0.8 and 0.9), and $\mathbf{S}_{\mathrm{D}}$ and $\mathbf{S}_{\mathrm{A}}$ 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 versus 0.3), which is much higher than the tipping point of 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 (e.g., 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. 2).

In Fig. 4, the focus is on the development of the connections between Mark and Jenny; 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 behavior 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 $\mathbf{RS}_{\mathrm{M,J},Y}$ of Jenny about Mark (the dark green line) and $\mathbf{RS}_{\mathrm{J,M},Y}$ 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 $\mathbf{RW}_{\mathrm{J,M},Y}$ 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 $\mathbf{RW}_{\mathrm{M,J},Y}$ 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.

5 Discussion

In this paper, computational analysis was made of the role of subjective elements and control in social network adaptation. It was analyzed: (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 behavior is as expected from the mentioned literature. Moreover, based on mathematical analysis, from formula (3) for the homophily function it can be predicted that when the model reaches equilibrium, it holds:

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

This is indeed the case, as can also be seen in the case study simulation in Fig. 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 behavior 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 behavior 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 [7, 9, 22] 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 [5, 6]. It can be an interesting challenge to explore how far a similar architecture for controlling social network adaptation as discussed in the current paper 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) in [2].

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