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Canbaloglu, Gülay; Treur, Jan; Roelofsma, Peter H.M.P.

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Chapter 6

Using Self-modeling Networks to Model Organisational Learning



Gülay Canbaloğlu, Jan Treur, and Peter H. M. P. Roelofsma

Abstract Within organisational learning literature, mental models are considered a vehicle for both individual learning and organisational learning. By learning individual mental models (and making them explicit), a basis for formation of shared mental models for the level of the organisation is created, which after its formation can then be adopted by individuals. This provides mechanisms for organisational learning. These mechanisms have been used as a basis for an adaptive computational network model. The model is illustrated by a not too complex but realistic case study.

Keywords Adaptive computational network model · Mental models · Organisational learning mechanisms

6.1 Introduction

Learning is an essential part of survival and has been a topic intensively studied. Organisational learning is a dynamic, multilevel and non-linear type of learning both involving individuals and independent of individuals. It is dynamic because it involves people, it is multilevel because the learning of organisation is different than all the individuals in the organisation, and it is non-linear because it has feedback mechanisms which provide individuals to learn from organisation. The concept of organisational learning has been addressed, for example, in (Argyris 1978; Bogenrieder 2002; Crossan 1999; Fischhof 1997; Kim 1993; McShane 2010; Stelmaszczyk

G. Canbaloğlu (✉) · J. Treur

Social AI Group, Department of Computer Science, Vrije Universiteit Amsterdam, Amsterdam, Netherlands

e-mail: gulaycnbl@gmail.com

J. Treur

e-mail: j.treur@vu.nl

P. H. M. P. Roelofsma

Center for Safety in Healthcare, Delft University of Technology, Delft, The Netherlands

e-mail: proelofsma@yahoo.co.uk

2016; Wiewiora 2019). Until recently the extensive literature on the concept of organisational learning had some deficiencies when it comes to computational models for it. However, in recent years a more detailed computational formalization of a clearly defined organisational learning process from beginning to end was developed. The study described in the current chapter, was the first in which a self-modeling network perspective was used to model the different processes and phases of organisational learning.

The transitions between individual and organisational learning are key points of understanding and directing the learning process of organisations (Kim 1993). Without any doubt, one of the most influential papers on organisational learning is (Kim 1993) with an impressive number of around 5000 citations in Google Scholar in 2022. The following quote illustrates in a summarized form the perspective sketched by Kim (1993):

Organisational learning is dependent on individuals improving their mental models; making those mental models explicit is crucial to developing new shared mental models. This process allows organisational learning to be independent of any specific individual. Why put so much emphasis on mental models? Because the mental models in individuals' heads are where a vast majority of an organisation's knowledge (both know-how and know-why) lies. (Kim 1993), p. 44

According to Kim, although there is a huge amount of previous research on learning, we are not able to fully understand the process itself (Kim 1993). Therefore, to comprehend and manage the formation of the common unified mental potential of a group, we need to work on organisational learning and its processes and phases. Computational modelling of organisational learning provides a more observable formalization of development steps of unified shared mental models. To this end, the network-oriented modeling approach based on self-modeling networks introduced in (Treur 2020a, b) that will be explained in detail in Sect. 6.3 was used in this current chapter. This modeling approach is at least as general as any other adaptive dynamical system modeling approach, as in (Hendrikse, Treur, Koole, 2023) it has been proven that any smooth adaptive dynamical system has a canonical representation as a self-modeling network. The paper by Kim (1993) was used as a point of departure and main source of inspiration for this chapter.

First, Sect. 6.2 presents how and in what aspects literature provides ideas on mental models and their role in organisational learning. Then, Sect. 6.3 explains the characteristics and details of adaptive self-modeling network models and how they can be used to model the different processes concerning dynamics, adaptation and control of mental models. In Sect. 6.4 the controlled adaptive network model for organisational learning is introduced. Then in Sect. 6.5, an example simulation scenario is explained in detail. In Sect. 6.6 equilibrium analysis of the introduced adaptive network model is provided. Section 6.7 is a Discussion section. Lastly, Sect. 6.8 is an appendix with a full specification of the model.

6.2 Background Literature

The topic addressed in this chapter involves a number of concepts and processes such as individual mental models and shared mental models, and how they are handled in order to obtain organisational learning. In this section, some of the multidisciplinary literature about these concepts and processes is briefly discussed. This provides a basis for the design choices made for the adaptive network model that will be presented in Sect. 6.4 and accordingly for the scientific justification of the model based on this multidisciplinary literature.

6.2.1 Mental Models

For the history of the mental model area, often Kenneth Craik is mentioned as a central person. In his book (Craik 1943), he describes a mental model as a *small-scale model* that is carried by an organism within its head as follows; see also (Williams 2018):

If the organism carries a “small-scale model” of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it. (Craik 1943, p. 61)

Note that this quote covers both the usage of a mental model based on so-called internal mental simulation (‘try out various alternatives’) and the learning of it (‘utilize the knowledge of past events’). Moreover, it also indicates how this contributes to safety when facing emergencies.

Other authors also have formulated what mental models are. For example, with an emphasis on causal relations, Shih and Alessi (1993, p. 157) explain that.

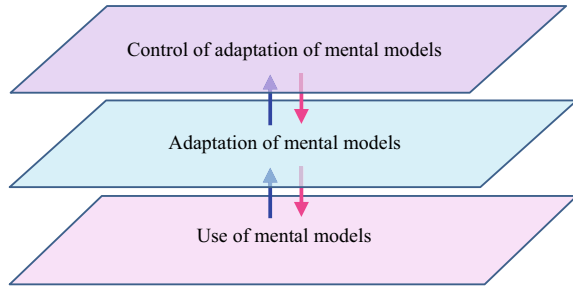
By a mental model we mean a person’s understanding of the environment. It can represent different states of the problem and the causal relationships among states.

De Kleer and Brown (1983) describe a mental model as the envisioning of a system, including a topological representation of the system components, the possible states of each of the components, and the structural relations between these components, the running or execution of the causal model based on basic operational rules and on general scientific principles.

An analysis of various types of mental models and the types of mental processes processing them can found in (Van Ments and Treur 2021). This analysis has led to a three-level cognitive architecture as depicted in Fig. 6.1 where:

- The base level models internal simulation of a mental model
- The middle level models the adaptation of the mental model (formation, learning, revising, and forgetting a mental model, for example)
- The upper-level models the (metacognitive) control over these processes

Fig. 6.1 Cognitive architecture for mental model handling with three levels of mental processing for mental models



Specific forms of learning that can be applied to mental models are observational learning (Yi and Davis 2003; Van Gog et al. 2009), instructional learning (Hogan 1997) and combinations thereof.

By using the notion of self-modeling network (or reified network) from (Treur 2020a, b), recently this cognitive architecture has been formalized computationally and used in computer simulations for many applications of mental models; for an overview of this approach and various applications of it, see (Treur and Van Ments 2022); see also Sect. 6.3.

6.2.2 Shared Mental Models

Mental models also play an important role when people work together in teams. When every team member has a different individual mental model of the task that is performed, then this will stand in the way of good teamwork. Therefore, ideally these mental models should be aligned to such an extent that it becomes one shared mental model for all team members.

Team errors have often been linked to inadequacies of the shared mental model and the lack of adaptivity of it (Fisschoff and Johnson 1997; Jones and Roelofsma 2000; Mathieu et al. 2000; Burthscher et al. 2011; Wilson 2019; Todd 2018). This has major implications for health care and patient safety in the operation room, e.g., concerning open heart operation and tracheal intubation (Higgs et al. 2018; Seo et al. 2021). Jones and Roelofsma (2000) discuss four types of team errors resulting from inadequate shared mental models.

The first is called ‘false consensus’. The false consensus effect (Ross et al. 1977; Kreuger 1998) refers to the tendency to overestimate the degree of similarity between self and other team members and this may result in biased judgements or team decisions. It is often described as people’s tendency to ‘see their own behavioural choices and judgements as relatively common and appropriate to existing circumstances while viewing alternative responses as uncommon, deviant, or inappropriate’.

A second type of team error and perhaps the most well-known is ‘groupthink’; e.g., (Janis 1972; Kleindorfer et al. 1993). It is often described as a mode of thinking that people engage in when they are deeply involved in a cohesive in-group, when the

members' striving for unanimity overrides their motivation to realistically appraise alternative courses of action. Groupthink refers to a deterioration of mental efficiency and reality testing that results from in-group pressures.

A third type of team error resulting from inadequate shared mental model is group polarization, e.g., (Lamm and Myers 1978; Isenberg 1986). This refers to the phenomenon that occurs when the position that is held on an issue by the majority of the group members is intensified as a result of discussion. For example, if group members are initially generally in favour of a particular preference of action, then group discussion will further enhance the favorability of this preference at an individual level. There are two special cases of group polarization. One is termed risky shift and occurs when a group, overall, becomes more risk seeking than the initial average risk seeking tendencies of the individual members. The other is termed cautious shift and occurs when groups become more risk averse than the initial average risk averse tendencies of the individual members. In both cases the average response of the individual group members is more extreme after discussion. Such shifts in preference have been demonstrated by an overwhelming number of studies.

A fourth team error is labelled escalation of commitment, e.g., (Bazerman 1984). This refers to the tendency for individuals or groups to continue to support a course of action despite evidence that it is failing. In other words, it is the tendency for a decision to support a previous decision for which there was a negative outcome. The specific concern is with non-rational escalation of commitment with a degree to which an individual escalates commitment to a previously selected course of action beyond a rational one.

An example of a computational model of a shared mental model and how imperfections in it work out can be found in (Van Ments et al. 2021). The model also uses the cognitive architecture for mental models depicted in Fig. 6.1 and its computational formalization addressed in (Treur and Van Ments 2022).

6.2.3 Organisational Learning: From Individual to Shared Mental Models and Back

Organisational learning is an area which has received much attention over time; see, for example, (Argyris 1978; Bogenrieder 2002; Crossan 1999; Fischhof 1997; Kim 1993; McShane 2010; Stelmaszczyk 2016; Wiewiora et al. 2019). However, contributions to computational formalization of organisational learning are very rare. The quote in the introduction section illustrates the perspective sketched by Kim (1993). Here, mental models are considered a vehicle for both individual learning and organisational learning. By learning individual mental models (and making them explicit), a basis for formation of shared mental models for the level of the organisation is created, which provides a mechanism for organisational learning. Inspired by this, the overall process consists of the following main processes and interactions (see also (Kim 1993), Fig. 6.8):

(a) Individual level

- (1) Creating and maintaining individual mental models
- (2) Choosing for a specific context a suitable individual mental model as focus
- (3) Applying a chosen individual mental model for internal simulation
- (4) Improving individual mental models (individual mental model learning)

(b) From individual level to organisation level

- (1) Deciding about creation of shared mental models
- (2) Creating shared mental models based on developed individual mental models

(c) Organisation level

- (1) Creating and maintaining shared mental models
- (2) Associating to a specific context a suitable shared mental model as focus
- (3) Improving shared mental models (shared mental model refinement or revision)

(d) From organisation level to individual level

- (1) Deciding about individuals to adopt shared mental models
- (2) Individuals adopting shared mental models by learning them

In terms of the cognitive architecture depicted in Fig. 6.1, applying a chosen individual mental model for internal simulation relates to the base level, improving the individual mental model relates to the middle level and choosing an individual mental model as focus relates to the upper level. Moreover, both interactions from individual to organisation level and vice versa involve changing (individual or shared) mental models and therefore relate to the middle level, while the deciding actions as a form of control relate to the upper level.

This overview will provide useful input to the design of the computational network model for organisational learning that will be introduced in Sect. 6.4.

6.3 The Self-Modeling Network Modeling Approach Used

In this section, the network-oriented modeling approach used is briefly introduced. Following (Treur 2020b), a temporal-causal network model is characterised by (here X and Y denote nodes of the network, also called states):

- *Connectivity characteristics*
Connections from a state X to a state Y and their weights $\omega_{X,Y}$
- *Aggregation characteristics*
For any state Y , some combination function $c_Y(..)$ defines the aggregation that is applied to the impacts $\omega_{X,Y}X(t)$ on Y from its incoming connections from states X

- *Timing characteristics*

Each state Y has a speed factor η_Y defining how fast it changes for given causal impact.

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

$$Y(t + \Delta t) = Y(t) + \eta_Y[\mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) - Y(t)]\Delta t \quad (6.1)$$

for any state Y and where X_1 to X_k are the states from which Y gets its incoming connections. Within the software environment described in (Treur 2020b, Ch. 9), a large number of currently around 65 useful basic combination functions are included in a combination function library. The above concepts enable to design network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. The examples of combination functions that are applied in the model introduced here can be found in Table 6.1.

Realistic network models are usually adaptive: Often not only their states but also some of their network characteristics change over time. By using a *self-modeling network* (also called a *reified* network), 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*) which represent (adaptive) network characteristics. In the graphical 3D-format as shown in Sect. 6.4, such additional states are depicted at a next level (called *self-model level* or *reification level*), where the original network is at the *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 $\mathbf{W}_{X,Y}$. 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. For example, an adaptive speed factor η_Y can be represented by a self-model state named \mathbf{H}_Y .

As the outcome of such a process of network reification is also a temporal-causal network model itself, as has been shown in (Treur 2020b, Ch 10), this self-modeling network construction can easily be applied iteratively to obtain multiple orders of self-models at multiple (first-order, second-order, ...) self-model levels. For example, a second-order self-model may include a second-order self-model state $\mathbf{H}_{\mathbf{W}_{X,Y}}$ representing the speed factor $\eta_{\mathbf{W}_{X,Y}}$ for the dynamics of first-order self-model state $\mathbf{W}_{X,Y}$ which in turn represents the adaptation of connection weight $\omega_{X,Y}$. Similarly, a persistence factor $\mu_{\mathbf{W}_{X,Y}}$ of such a first-order self-model state $\mathbf{W}_{X,Y}$ used for adaptation (e.g., based on Hebbian learning) can be represented by a second-order self-model state $\mathbf{M}_{\mathbf{W}_{X,Y}}$.

In the current chapter, this multi-level self-modeling network perspective will be applied to obtain a second-order adaptive mental network architecture addressing the mental and social processes underlying organisational learning by proper handling of individual mental models and shared mental models. In this self-modeling network

Table 6.1 The combination functions used in the introduced network model

	Notation	Formula	Parameters
Advanced logistic sum	alogistic $_{\sigma,\tau}(V_1, \dots, V_k)$	$[\frac{1}{1+e^{-\sigma(V_1+\dots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}}](1 + e^{-\sigma\tau})$	Steepness $\sigma > 0$ Excitability threshold τ
Steponce	steponce $_{\alpha,\beta}(\dots)$	1 if time t is between α and β , else 0	Start time α End time β
Hebbian learning	hebb $_{\mu}(V_1, V_2, V_3)$	$V_1 * V_2(1 - V_3) + \mu V_3$	V_1, V_2 activation levels of the connected states; V_3 activation level of the self-model state for the connection weight Persistence factor μ
Maximum composed with Hebbian learning	max-hebb $_{\mu}(V_1, \dots, V_k)$	$\max(\text{hebb}_{\mu}(V_1, V_2, V_3), V_4, \dots, V_k)$	V_1, V_2 activation levels of the connected states; V_3 activation level of the self-model state for the connection weight Persistence factor μ
Scaled maximum	smax $_{\lambda}(V_1, \dots, V_k)$	$\max(V_1, \dots, V_k)/\lambda$	Scaling factor λ

architecture the base level addresses the use of a mental model by internal simulation, the first-order self-model the adaptation of the mental model, and the second-order self-model level the control over this; see Fig. 6.2. In this way the three-level cognitive architecture depicted in Fig. 6.1 is formalized computationally in the form of a self-modeling network architecture.

In (Bhalwankar and Treur 2021a, b) it is shown how specific forms of learning and their control can be modeled based on this self-modeling network architecture, in particular observational learning (Yi and Davis 2003; Van Gog et al. 2009) and instructional learning (Hogan 1997) and combinations thereof. Such forms of learning will also be applied in the model for organisational learning introduced here in Sect. 6.4.

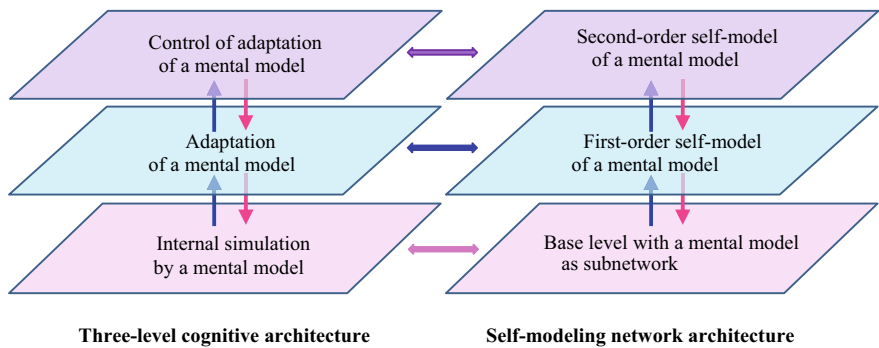


Fig. 6.2 Computational formalization of the three-level cognitive architecture for mental model handling from Fig. 6.1 by a self-modeling network architecture

6.4 The Adaptive Network Model for Organisational Learning

The case study addressed to illustrate the introduced model was adopted from the more extensive case study in an intubation process from (Van Ments et al. 2021a, b). Here only the part of the mental models is used that addresses four mental states; see the red outlined parts in Fig. 6.3 and the explanations in Table 6.2.

In the case study addressed here, initially the mental models of the nurse (person A) and doctor (person B) are different and based on weak connections; they don't use a stronger shared mental model as that does not exist yet. The organisational learning addressed to improve the situation covers:

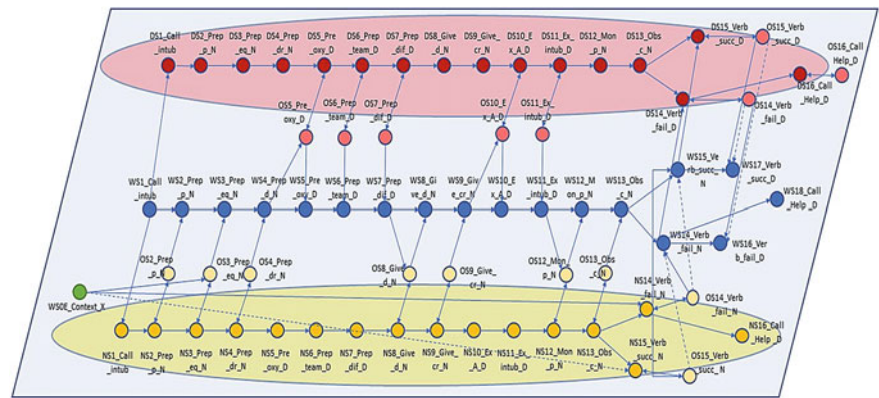


Fig. 6.3 The example mental model from (Van Ments et al. 2021a, b) with indicated the part used in the current chapter

Table 6.2 The mental model used for the simple case study

States for mental models of persons A, B and organisation O			Short notation	Explanation
a_A	a_B	a_O	Prep_eq_N	Preparation of the intubation equipment by the nurse
b_A	b_B	b_O	Prep_d_N	Nurse prepares drugs for the patient
c_A	c_B	c_O	Pre_oy_D	Doctor executes pre oxygenation
d_A	d_B	d_O	Prep_team_D	Doctor prepares the team for intubation

1. Individual learning by A and B of their mental models through internal simulation which results in stronger but still incomplete and different mental models (by Hebbian learning). Person A's mental model has no connection from c_A to d_A and person B's mental model has no connection from a_B to b_B.
2. Formation of a shared organisation mental model based on the two individual mental models. A process of unification takes place.
3. Learning individual mental models from the shared mental model, e.g., a form of instructional learning.
4. Strengthening these individual mental models by individual learning through internal simulation which results in stronger and now complete mental models (by Hebbian learning). Now person A's mental model has a connection from c_A to d_A and person B's mental model has a connection from a_B to b_B.

The connectivity of the designed network model is depicted in Fig. 6.4; for an overview of the states, see Figs. 6.5, 6.6, 6.7. For more details about the connections and how they relate to (a) to (d) from Sect. 6.2.3, see Fig. 6.8.

In this model, at the base level individual mental states of persons and shared mental model states of the organisation involving these people are placed. The context states used for initiation of different processes or phases are also in this base level plane. These states can be considered as the core of the model representing knowledge of people and organisation's general level of knowledge on separate tasks. The mental states of persons are connected to each other, which reflects the knowledge about the temporal order between tasks and the first ones have a connection from the first context state to be initiated in the first phase. Their 'hollow' mental states, the tasks that they do not know, have connections also from the fourth context state to be able to observe the progress of these states.

First- and second-order self-model states are used to bring multi-order adaptivity to the network model. The first-order adaptation level provides adaptivity of the base level and the second-order one controls this adaptivity. In the first-order self-model level, **W**-states for all the weights of the connections between the base level states are placed. In the first place, these are the adaptive weights of the base level individual mental state connections of persons. In addition, there are **W**-states of the developed shared organisation mental model states. At this first-order adaptation level there are (intralevel) connections from all the **W**-states (two for this case) that specify the

Nr	State	Explanation
X ₁₇	\mathbf{W}_{a_A,b_A}	First-order self-model state for the weight of the connection from a to b within the individual mental model of person A
X ₁₈	\mathbf{W}_{b_A,c_A}	First-order self-model state for the weight of the connection from b to c within the individual mental model of person A
X ₁₉	\mathbf{W}_{c_A,d_A}	First-order self-model state for the weight of the connection from c to d within the individual mental model of person A
X ₂₀	\mathbf{W}_{a_B,b_B}	First-order self-model state for the weight of the connection from a to b within the individual mental model of person B
X ₂₁	\mathbf{W}_{b_B,c_B}	First-order self-model state for the weight of the connection from b to c within the individual mental model of person B
X ₂₂	\mathbf{W}_{c_B,d_B}	First-order self-model state for the weight of the connection from c to d within the individual mental model of person B
X ₂₃	\mathbf{W}_{a_O,b_O}	First-order self-model state for the weight of the connection from a to b within the shared mental model of the organisation O
X ₂₄	\mathbf{W}_{b_O,c_O}	First-order self-model state for the weight of the connection from b to c within the shared mental model of the organisation O
X ₂₅	\mathbf{W}_{c_O,d_O}	First-order self-model state for the weight of the connection from c to d within the shared mental model of the organisation O

Fig. 6.6 First-order self-model states of the introduced adaptive network model

adaptation speeds of connection weights in the first-order adaptation level, and \mathbf{M}_w -states for persistence of adaptation. This provides the speed and persistence control of the adaptation.

6.5 Example Simulation Scenario

In this scenario, a multi-phase approach is applied to observe two separate individual mental models first, formation and effects of the created shared mental model for the organisation then. Thus, it is possible to explore how organisational learning progresses. Note that these processes are structured in phases to get a clear picture of what happens. In practice and also in the model, these processes also can overlap or take place entirely simultaneously. The four phases were designed as follows:

- **Phase 1: Individual mental model usage and learning**

This relates to (a) in Sect. 6.2.3. Two distinct mental models representing two different employees in the same group or organisation are constructed here. Persons have both common and special characteristics and knowledge. For the specific scenario, persons A and B are the employees of an organisation. Initially they have a weak mental model for their job considered here but by (Hebbian) learning their mental models strengthen over time during usage of them for internal simulation. They are involved in the same job, but A does the first part of the job while B finishes it. Therefore, in this phase A does not have the knowledge of the end part of the job, and B does not know how to start the job. Moreover, their characteristics are different in terms of persistence of the learning. The values of

Nr	State	Explanation
X ₂₆	$\mathbf{W}_{\mathbf{w}_{a_O,b_O}, \mathbf{w}_{a_A,b_A}}$	Second-order self-model state for the weight of the connection from shared mental model connection weight self-model state \mathbf{W}_{a_O,b_O} to individual mental model connection weight self-model state \mathbf{W}_{a_A,b_A} for instructional learning of the shared mental model
X ₂₇	$\mathbf{W}_{\mathbf{w}_{b_O,c_O}, \mathbf{w}_{b_A,c_A}}$	Second-order self-model state for the weight of the connection from shared mental model connection weight self-model state \mathbf{W}_{b_O,c_O} to individual mental model connection weight self-model state \mathbf{W}_{b_A,c_A} for instructional learning of the shared mental model
X ₂₈	$\mathbf{W}_{\mathbf{w}_{c_O,d_O}, \mathbf{w}_{c_A,d_A}}$	Second-order self-model state for the weight of the connection from shared mental model connection weight self-model state \mathbf{W}_{c_O,d_O} to individual mental model connection weight self-model state \mathbf{W}_{c_A,d_A} for instructional learning of the shared mental model
X ₂₉	$\mathbf{W}_{\mathbf{w}_{a_O,b_O}, \mathbf{w}_{a_B,b_B}}$	Second-order self-model state for the weight of the connection from shared mental model connection weight self-model state \mathbf{W}_{a_O,b_O} to individual mental model connection weight self-model state \mathbf{W}_{a_B,b_B} for instructional learning of the shared mental model
X ₃₀	$\mathbf{W}_{\mathbf{w}_{b_O,c_O}, \mathbf{w}_{b_B,c_B}}$	Second-order self-model state for the weight of the connection from shared mental model connection weight self-model state \mathbf{W}_{b_O,c_O} to individual mental model connection weight self-model state \mathbf{W}_{b_B,c_B} for instructional learning of the shared mental model
X ₃₁	$\mathbf{W}_{\mathbf{w}_{c_O,d_O}, \mathbf{w}_{c_B,d_B}}$	Second-order self-model state for the weight of the connection from shared mental model connection weight self-model state \mathbf{W}_{c_O,d_O} to individual mental model connection weight self-model state \mathbf{W}_{c_B,d_B} for instructional learning of the shared mental model
X ₃₂	$\mathbf{H}_{\mathbf{w}_{a_A,b_A}}$	Second-order self-model state for the adaptation speed of individual mental model connection weight self-model state \mathbf{W}_{a_A,b_A}
X ₃₃	$\mathbf{H}_{\mathbf{w}_{b_A,c_A}}$	Second-order self-model state for the adaptation speed of individual mental model connection weight self-model state \mathbf{W}_{b_A,c_A}
X ₃₄	$\mathbf{H}_{\mathbf{w}_{c_A,d_A}}$	Second-order self-model state for the adaptation speed of individual mental model connection weight self-model state \mathbf{W}_{c_A,d_A}
X ₃₅	$\mathbf{H}_{\mathbf{w}_{a_B,b_B}}$	Second-order self-model state for the adaptation speed of individual mental model connection weight self-model state \mathbf{W}_{a_B,b_B}
X ₃₆	$\mathbf{H}_{\mathbf{w}_{b_B,c_B}}$	Second-order self-model state for the adaptation speed of individual mental model connection weight self-model state \mathbf{W}_{b_B,c_B}
X ₃₇	$\mathbf{H}_{\mathbf{w}_{c_B,d_B}}$	Second-order self-model state for the adaptation speed of individual mental model connection weight self-model state \mathbf{W}_{c_B,d_B}
X ₃₈	$\mathbf{H}_{\mathbf{w}_{a_O,b_O}}$	Second-order self-model state for the adaptation speed of shared mental model connection weight self-model state \mathbf{W}_{a_O,b_O} for formation or revision of the shared mental model
X ₃₉	$\mathbf{H}_{\mathbf{w}_{b_O,c_O}}$	Second-order self-model state for the adaptation speed of shared mental model connection weight self-model state \mathbf{W}_{b_O,c_O} for formation or revision of the shared mental model
X ₄₀	$\mathbf{H}_{\mathbf{w}_{c_O,d_O}}$	Second-order self-model state for the adaptation speed of shared mental model connection weight self-model state \mathbf{W}_{c_O,d_O} for formation or revision of the shared mental model
X ₄₁	$\mathbf{M}_{\mathbf{w}_{a_A,b_A}}$	Second-order self-model state for persistence of adaptation of individual mental model connection weight self-model state \mathbf{W}_{a_A,b_A}
X ₄₂	$\mathbf{M}_{\mathbf{w}_{b_A,c_A}}$	Second-order self-model state for persistence of adaptation of individual mental model connection weight self-model state \mathbf{W}_{b_A,c_A}
X ₄₃	$\mathbf{M}_{\mathbf{w}_{c_A,d_A}}$	Second-order self-model state for persistence of adaptation of individual mental model connection weight self-model state \mathbf{W}_{c_A,d_A}
X ₄₄	$\mathbf{M}_{\mathbf{w}_{a_B,b_B}}$	Second-order self-model state for persistence of adaptation of individual mental model connection weight self-model state \mathbf{W}_{a_B,b_B}
X ₄₅	$\mathbf{M}_{\mathbf{w}_{b_B,c_B}}$	Second-order self-model state for persistence of adaptation of individual mental model connection weight self-model state \mathbf{W}_{b_B,c_B}
X ₄₆	$\mathbf{M}_{\mathbf{w}_{c_B,d_B}}$	Second-order self-model state for persistence of adaptation of individual mental model connection weight self-model state \mathbf{W}_{c_B,d_B}

Fig. 6.7 Second-order self-model states of the introduced adaptive network model

Intralevel connections		
$x_Z \rightarrow y_Z$	Connection from x to y in individual mental model of person Z : (a) from Sect. 2.3.	
$x_O \rightarrow y_O$	Connection from x to y in shared mental model of organisation O : (a) from Sect. 2.3.	
$con_p \rightarrow x_Z$	Connection from context state con_p for phase $p \in \{ph1, ph4\}$ to activate mental model state x of person Z : (c) from Sect. 2.3.	
$W_{x_Zy_Z} \rightarrow W_{x_Oy_O}$	Connection for person Z 's contribution from the weight of the connection from x to y in the individual mental model of Z to the weight of the connection from x to y in the shared mental model of O : (b) from Sect. 2.3.	
$W_{x_Oy_O} \rightarrow W_{x_Zy_Z}$	Connection for O 's contribution from the weight of the connection from x to y in the shared mental model of O to the weight of the connection from x to y in the individual mental model of person Z : (d) from Sect. 2.3.	
$W_{x_Zy_Z} \rightarrow W_{x_Zy_Z}$	Persistence connection for Z 's mental model connections: (a) from Sect. 2.3.	
Interlevel connections		
$x_Z \rightarrow W_{x_Zy_Z}$	Connection for individual Hebbian learning from state x in person Z 's individual mental model to self-model state $W_{x_Ay_A}$ for Z 's individual mental model: (a) from Sect. 2.3.	Upward from base level to first self-model level
$y_Z \rightarrow W_{x_Zy_Z}$	Connection for individual Hebbian learning from state y in person Z 's individual mental model to self-model state $W_{x_Ay_A}$ for Z 's individual mental model: (a) from Sect. 2.3.	
$x_O \rightarrow W_{x_Oy_O}$	Connection for Hebbian learning from state x in O 's shared mental model to self-model state $W_{x_Ay_A}$ for O 's shared mental model: (c) from Sect. 2.3.	
$y_O \rightarrow W_{x_Oy_O}$	Connection for Hebbian learning from state y in O 's shared mental model to self-model state $W_{x_Ay_A}$ for O 's shared mental model: (c) from Sect. 2.3.	
$W_{x_Zy_Z} \rightarrow y_Z$	Connection for the effect of self-model state $W_{x_Zy_Z}$ for person Z 's individual mental model on state y in Z 's individual mental model: (a) from Sect. 2.3.	Downward from first-order self-model level to base level
$W_{x_Oy_O} \rightarrow y_O$	Connection for the effect of self-model state $W_{x_Oy_O}$ for O 's shared mental model on state y in O 's shared mental model: (c) from Sect. 2.3.	
$con_{ph2} \rightarrow H_{W_{x_Oy_O}}$	Connection from the context state for Phase 2 to second-order self-model state $H_{W_{x_Oy_O}}$ representing the adaptation speed of first-order self-model state $W_{x_Oy_O}$ for the weight of the connection from x to y in the shared mental model of O in order to trigger this adaptation speed for shared mental model formation: (b) from Sect. 2.3.	Upward from base level to second-order self-model level
$con_{ph3} \rightarrow W_{x_Oy_O, W_{x_Zy_Z}}$	Connection from the context state for Phase 3 to second-order self-model state $W_{W_{x_Oy_O}, W_{x_Zy_Z}}$ representing the weight of the connection from first-order self-model state $W_{x_Oy_O}$ for the weight of the connection from x to y in the shared mental model of O to first-order self-model state $W_{x_Zy_Z}$ for the weight of the connection from x to y in the individual mental model of person Z in order to activate this connection for instructional learning of Z from the shared mental model: (d) from Sect. 2.3.	
$H_{W_{x_Oy_O}} \rightarrow W_{x_Oy_O}$	Effectuation of control of the adaptation of O 's shared mental model connection weight $W_{x_Oy_O}$ for shared mental model formation based on Z 's individual mental model: (b) , (c) from Sect. 2.3.	Downward from second-order self-model level
$W_{W_{x_Oy_O}, W_{x_Zy_Z}} \rightarrow W_{x_Zy_Z}$	Effectuation of control of the adaptation of person Z 's individual mental model connection weight $W_{x_Zy_Z}$ for instructional learning of Z 's individual mental model from O 's shared mental model: (d) from Sect. 2.3.	

Fig. 6.8 Types of connections in the adaptive network model and how they relate to **(a)** to **(d)** identified in Sect. 6.2.3. For the example scenario, x and y are states from $\{a, b, c, d\}$ and Z is a person from $\{A, B\}$

person A 's M -states are slightly higher than B 's. It means that B forgets things faster than A .

- **Phase 2: Shared mental model formation**

This relates to **(b)** and **(c)** in Sect. 6.2.3. Formation of the unified shared mental model of the employees occurs in this phase. This takes place by a form of aggregation and unification of the individual mental models. The collaboration of the employees starts the process of organisational learning, and the values of the **W**-states of the shared mental model for the general (non-personal) states for the job (a_O to d_O) increase. Then this shared mental model is maintained by the organisation.

- **Phase 3: Instructional learning of the shared mental model by the individuals**

This relates to **(d)** in Sect. 6.2.3. The connections from the general **W**-states of the shared mental model to the personal **W**-states of the individuals are activated, and knowledge from the shared mental model is received here as a form of instructional learning. Persons start to learn from the organisation's unified shared mental model, for this scenario, which can be considered as learning from each other in an indirect manner via the shared mental model. Since there is only one shared mental model, this does not require many mutual one-to-one interactions between employees.

- **Phase 4: Individual mental model usage and learning**

This relates to **(d)** in Sect. 6.2.3. In this phase, employees have the chance of further improving their mental models (in Phase 3 already improved based on the shared mental model) by the help of Hebbian learning during usage of the mental model for internal simulation. Person A starts to learn about task d (state d_A) by using the knowledge of person B (obtained via the shared mental model) and similarly B learns about task a (state a_B) that they did not know in the beginning. Therefore, these 'hollow' states become meaningful for the individuals. The individuals take advantage of the organisational learning.

Figure 6.9 shows an overview of all states of the simulation; Figs. 6.10, 6.11 focus on part of the states (for the same simulation) to get a more detailed view.

In Fig. 6.10 it can be seen that the activation levels of person A's mental model states X_1 , X_2 and X_3 (a_A to c_A) increase in Phase 1 between time 10 and 300 while the activation level of X_4 (d_A) remains at zero because A does not have knowledge on this state d in the beginning. The latter state will increase in Phase 4 after learning in Phase 3 from the unified shared mental model developed in Phase 2.

Person B's mental model states X_6 , X_7 and X_8 (b_B to d_B) increase just like A's in phase 1, while the activation level of X_5 (a_B) remains at zero because B does not have knowledge of this state a in the beginning. It will also increase in Phase 4 after learning in Phase 3 from the unified shared model developed in Phase 2.

The values of person A's **W**-states X_{17} and X_{18} representing A's mental model connection weights W_{a_A, b_A} and W_{b_A, c_A} increase in the first phase, meaning that A learns the mental model better by using it for internal simulation (Hebbian learning). However, they slightly decrease in the second phase at about 300–400 since the persistence factor self-model **M**-state of A has not the perfect value 1, meaning that A forgets. Person B's **W**-states X_{21} and X_{22} representing B's mental model

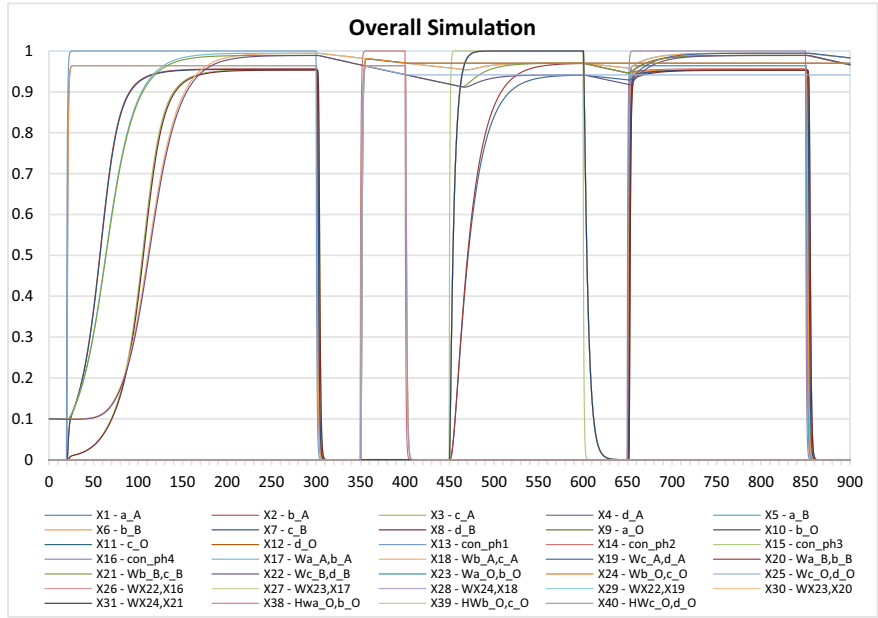


Fig. 6.9 Simulation graph showing all states

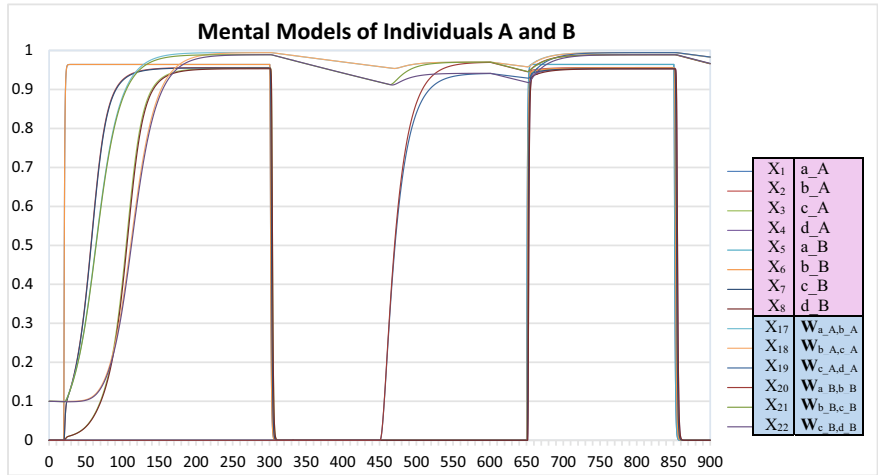


Fig. 6.10 The base states and connection weight self-model states for the individual mental models

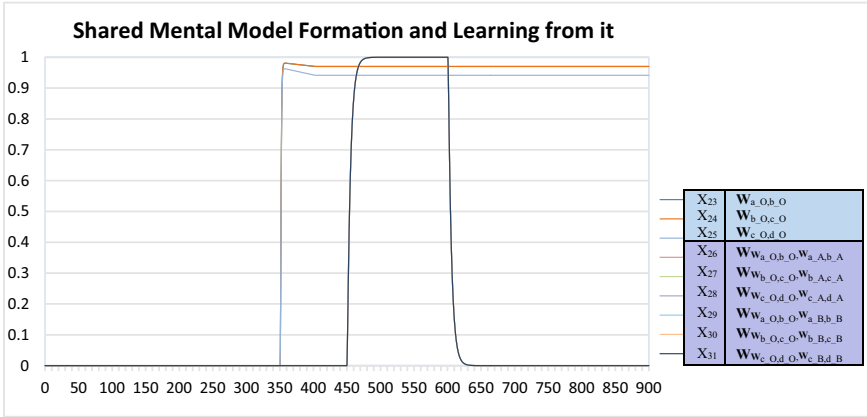


Fig. 6.11 The connection weight self-model states for the shared mental model and the weights by which individuals receive instructional learning of the shared mental model

connections $W_{b,B,c,B}$ and $W_{c,B,d,B}$ follow a similar pattern but since the persistence factor of B is smaller than of A, they decrease more in the second phase: it can be observed that B is a more forgetful person.

State X_{19} ($W_{c,A,d,A}$) is the W -state for the connection from c_A to d_A within A's mental model. Because A does not have a nonzero X_4 state in the beginning, learning can happen only (by instructional learning in Phase 3) after a unified shared mental model has been formed (in Phase 2). Thus, X_{19} increases in Phase 3 at about time 450. Same is valid for X_{20} , the W -state for the connection from a_B to b_B within B's mental model. This addresses the task a that B does not know about in the beginning.

By observing in Fig. 6.10 Phase 4 after time 650, it can be seen that all the W -states of the individuals make an upward jump. The reason for this is the main focus of this chapter, organisational learning. As will be explained in more detail in the following paragraph, the W -states of the organisation's shared mental model have links back to the W -states of the individuals' mental models to provide the ability of individuals to learn (by instructional learning) from the shared mental model.

As can be seen in Fig. 6.11, all the second-order self-model W -states (X_{26} to X_{31}) for connections from the unified shared mental model's W -states to the individuals' W -states become activated in Phase 3 between 450 and 650. This models the instructional learning: the persons are informed about the shared mental model. Because the characteristics involved have the same values in the role matrices, they trace the same curve. The unified shared mental model gains its characteristics in the second phase at around 350 by the help of a form of aggregation of the W -states of the mental models of the employees A and B. As also can be seen in Fig. 6.11, states X_{23} , X_{24} and X_{25} (shared mental model connection weight self-model states $W_{a,O,b,O}$, $W_{b,O,c,O}$, and $W_{c,O,d,O}$) jump upward in this phase to form the unified

shared mental model, and during the phase they decrease a little bit because of the forgetting of the employees.

6.6 Mathematical Analysis of Equilibria of the Network Model

In general, a dynamical system is in equilibrium at time t if $dY(t)/dt = 0$ for all of its state variables Y . The same can be applied to self-modeling network models. However, given the standard Eq. (6.1) in terms of the network characteristics, for network models the condition $dY(t)/dt = 0$ can be formulated as the following criterion

$$\mu_Y = 0 \quad \text{or} \quad c_Y(\omega_{X_1,Y} X_1(t), \dots, \omega_{X_k,Y} X_k(t)) = Y(t) \quad (6.2)$$

This can be used to verify if the implemented model is correct with respect to the design of the model. As an example, consider the adaptation of the weights according to the combination function **max-hebb** defined in Table 6.1.

$$\mathbf{max-hebb}_\mu(V_1, \dots, V_k) = \max(\mathbf{hebb}_\mu(V_1, V_2, V_3), V_4, \dots, V_k) \quad (6.3)$$

where

$$\mathbf{hebb}_\mu(V_1, V_2, V_3) = V_1 * V_2(1 - V_3) + \mu V_3$$

Therefore, for this case the above criterion for being in an equilibrium state is equivalent to

$$\eta_Y = 0 \quad \text{or} \quad \max(V_1 * V_2(1 - V_3) + \mu V_3, V_4, \dots, V_k) = Y(t) \quad (6.4)$$

One of the states to which this combination function is applied (with $k = 4$) is \mathbf{W}_{b_A,c_A} , which is X_{18} . It has incoming connections from b_A, c_A (X_2, X_3) and X_{18} itself (all three with connection weights 1), and from X_{24} (with adaptive connection weight represented by self-modeling state $\mathbf{W}_{w_{b_O,c_O}, w_{b_A,c_A}}$ which is X_{27}). Moreover, $\mu = 0.995$. From the simulation results it seems that this state is (approximately) stationary at time $t = 299$ and at time $t = 849$. The speed factor η of \mathbf{W}_{b_A,c_A} is 0.05 which is nonzero. The values for the relevant states from the simulation at these time points are the following:

$$V_1 = X_2(299) = 0.956268089647092$$

$$V_2 = X_3(299) = 0.954552603376293$$

$$V_3 = X_{18}(299) = 0.994443719684304$$

$$V_4 = X_{24}(299) = 0$$

$$\mu = 0.995$$

If these values are substituted in (4) we get the following

$$\max(V_1 * V_2(1 - V_3) + V_3, V_4, \dots, V_k) = 0.994543319288979$$

$$Y(299) = 0.994443719684304$$

These two values show a deviation of 0.0000996 which is less than 10^{-4} . This quite good approximation of the equation in (4) provides evidence that the implemented model is correct with respect to its design. Similarly, for $t = 849$:

$$V_1 = X_2(849) = 0.956269533716948$$

$$V_2 = X_3(849) = 0.95457581935179$$

$$V_3 = X_{18}(849) = 0.994548119402481$$

$$V_4 = X_{24}(849) = 0.970297110356546$$

$$\mu = 0.995$$

If these values are substituted in (4) we get the following

$$\max(V_1 * V_2(1 - V_3) + V_3, V_4, \dots, V_k) = 0.994552028641134$$

$$Y(849) = 0.994548119402481$$

These two values show a deviation of 0.00000391, which is less than 10^{-5} . This again quite good approximation of the equation in (4) provides still more evidence that the implemented model is correct with respect to its design.

6.7 Discussion

This chapter is based on material from (Canbaloğlu et al. 2022). Organisational learning is a complex process that is challenging when computational modeling of it is concerned; computational models of organisational learning are practically absent in the literature. Within mainstream organisational learning literature such as (Kim 1993; Wiewiora et al. 2019), (individual and shared) mental models are considered to be a vehicle for both individual learning and organisational learning. By learning individual mental models, sources for the formation of shared mental models for the level of the organisation as a whole are created. Once these shared organisation mental models have been formed, they are available to be adopted by individuals within the organisation by learning and applying them. This combination of individual mental model learning—shared mental model formation—individual (shared) mental model adoption, and some others indicates a handful of mechanisms of different types that together can be considered to form the basis of organisational learning. The challenges then are (1) to formalize these mechanisms in a computational manner, and (2) to glue them together according to a suitable type of architecture.

These mechanisms indeed have been used as a basis for the designed adaptive computational network model. The model was illustrated by a not too complex but realistic case study. Note that for the sake of presentation, in the case study scenario the different types of mechanisms have been structured over time sequentially. This is not inherent in the designed computational network model itself. All these processes can equally well work simultaneously in parallel.

The introduced computational model for organisational learning has been designed as a second-order adaptive network model according to the modeling approach based on self-modeling network models described in (Treur 2020b). Here, the three-level cognitive architecture for handling mental models as described in (Van Ments and Treur 2021) was adopted and formalized computationally as a self-modeling network architecture, where the first-order self-model level models the adaptation of weights of connections within mental models and the second-order self-model level models the control over this adaptation. These weights can be adapted in different manners, depending on the context. One context for adapting them is for the focusing on a specific mental model as, for example, is addressed in (Canbaloğlu and Treur 2021). Another context for adaptation is for Hebbian learning as applied during internal mental simulation in (Canbaloğlu et al. 2022) and in (Bhalwankar and Treur 2021) during observational learning. These different types of adaptation were also adopted in the adaptive network for organisational learning introduced in the current chapter. Thereby, the context-sensitive control of them was modeling by the second-order self-model level.

For this first step in computational formalization of organisational learning by an adaptive network model as presented here, a number of issues have been left out of consideration yet. The model provides a good basis to address these in future work, thereby obtaining extensions or refinements of the model.

One of these extension possibilities concerns the type of aggregation used for the process of shared mental model formation. In the current model this has been based on the person who has maximal knowledge about a specific mental model connection. But other forms of aggregation can equally well be applied, for example weighted averages. Moreover, the choice of aggregation can be made adaptive in a context-sensitive manner so that for each context a different form of aggregation can be chosen automatically as part of the overall process. Also, aspects of priorities for the importance or reliability of individual mental models compared to each other may be incorporated.

Another extension is to make other states used for the control adaptive and context-sensitive, such as the second-order self-model **H**- and **M**-states for the individuals, which for the sake of simplicity were kept constant in the current example scenario. A third option to extend the model is by adding states for the actual actions in the world and for observational learning based on such actions observed in the world, such as for example addressed in (Bhalwankar and Treur 2021).

Finally, yet another option for an extension is to add an intermediate level of teams in between the individual and organisational level as, for example, discussed in (Wiewiora et al. 2019). In contrast to the current chapter, which used the paper by Kim (1993) as a point of departure and main source of inspiration for this chapter, In Chap. 7 of this volume (Canbaloglu et al. 2023), this intermediate level will be addressed in addition.

6.8 Appendix: Full Specification by Role Matrices

In this section, the different role matrices are shown that provide a full specification of the network characteristics defining the adaptive network model in a standardised table format. Here in each role matrix, each state has its row where it is listed which are the impacts on it from that role.

6.8.1 Role Matrices for Connectivity Characteristics

The connectivity characteristics are specified by role matrices **mb** and **mcw** shown in Figs. 6.12, 6.13. Role matrix **mb** lists the other states (at the same or lower level) from which the state gets its incoming connections, whereas in role matrix **mcw** the connection weights are listed for these connections.

Nonadaptive connection weights are indicated in **mcw** (in Fig. 6.13) by a number (in a green shaded cell), but adaptive connection weights are indicated by a reference to the (self-model) state representing the adaptive value (in a peach-red shaded cell). This can be seen for states X_2 to X_4 (with self-model states X_{17} to X_{19}), states X_6 to X_8 (with self-model states X_{20} to X_{22}), X_{10} to X_{12} (with self-model states X_{23} to X_{25}), and X_{17} to X_{22} (with self-model states X_{26} to X_{31}).

mb base		1	2	3	4	5	6	7
connectivity								
X ₁	a_A	X ₁₃	X ₁₆					
X ₂	b_A	X ₁						
X ₃	c_A	X ₂						
X ₄	d_A	X ₃						
X ₅	a_B	X ₁₆						
X ₆	b_B	X ₅	X ₁₃					
X ₇	c_B	X ₆						
X ₈	d_B	X ₇						
X ₉	a_O							
X ₁₀	b_O	X ₉						
X ₁₁	c_O	X ₁₀						
X ₁₂	d_O	X ₁₁						
X ₁₃	c _{ph1}	X ₁₃						
X ₁₄	c _{ph2}	X ₁₄						
X ₁₅	c _{ph3}	X ₁₅						
X ₁₆	c _{ph4}	X ₁₆						
X ₁₇	W _a A,b A	X ₁	X ₂	X ₁₇	X ₂₃			
X ₁₈	W _b A,c A	X ₂	X ₃	X ₁₈	X ₂₄			
X ₁₉	W _c A,d A	X ₃	X ₄	X ₁₉	X ₂₅			
X ₂₀	W _a B,b B	X ₅	X ₆	X ₂₀	X ₂₃			
X ₂₁	W _b B,c B	X ₆	X ₇	X ₂₁	X ₂₄			
X ₂₂	W _c B,d B	X ₇	X ₈	X ₂₂	X ₂₅			
X ₂₃	W _a O,b O	X ₁₇	X ₂₀					
X ₂₄	W _b O,c O	X ₁₈	X ₂₁					
X ₂₅	W _c O,d O	X ₁₉	X ₂₂					
X ₂₆	Ww _a O,b O, w _a A,b A	X ₂₃	X ₁₇	X ₁₃	X ₁₄	X ₁₅		
X ₂₇	Ww _b O,c O, w _b A,c A	X ₂₄	X ₁₈	X ₁₃	X ₁₄	X ₁₅		
X ₂₈	Ww _c O,d O, w _c A,d A	X ₂₅	X ₁₉	X ₁₃	X ₁₄	X ₁₅		
X ₂₉	Ww _a O,b O, w _a B,b B	X ₂₃	X ₂₀	X ₁₃	X ₁₄	X ₁₅		
X ₃₀	Ww _b O,c O, w _b B,c B	X ₂₄	X ₂₁	X ₁₃	X ₁₄	X ₁₅		
X ₃₁	Ww _c O,d O, w _c B,d B	X ₂₅	X ₂₂	X ₁₃	X ₁₄	X ₁₅		
X ₃₂	Hw _a A,b A	X ₁	X ₂	X ₁₇	X ₃₂			
X ₃₃	Hw _b A,c A	X ₂	X ₃	X ₁₈	X ₃₃			
X ₃₄	Hw _c A,d A	X ₃	X ₄	X ₁₉	X ₃₄			
X ₃₅	Hw _a B,b B	X ₅	X ₆	X ₂₀	X ₃₅			
X ₃₆	Hw _b B,c B	X ₆	X ₇	X ₂₁	X ₃₆			
X ₃₇	Hw _c B,d B	X ₇	X ₈	X ₂₂	X ₃₇			
X ₃₈	Hw _a O,b O	X ₁₄						
X ₃₉	Hw _b O,c O	X ₁₄						
X ₄₀	Hw _c O,d O	X ₁₄						
X ₄₁	Mw _a A,b A	X ₁	X ₂	X ₁₇	X ₄₁	X ₁₃	X ₁₄	X ₁₅
X ₄₂	Mw _b A,c A	X ₂	X ₃	X ₁₈	X ₄₂	X ₁₃	X ₁₄	X ₁₅
X ₄₃	Mw _c A,d A	X ₃	X ₄	X ₁₉	X ₄₃	X ₁₃	X ₁₄	X ₁₅
X ₄₄	Mw _a B,b B	X ₅	X ₆	X ₂₀	X ₄₄	X ₁₃	X ₁₄	X ₁₅
X ₄₅	Mw _b B,c B	X ₆	X ₇	X ₂₁	X ₄₅	X ₁₃	X ₁₄	X ₁₅
X ₄₆	Mw _c B,d B	X ₇	X ₈	X ₂₂	X ₄₆	X ₁₃	X ₁₄	X ₁₅

Fig. 6.12 Role matrices for the connectivity: **mb** for base connectivity

mcw		connection weights						
		1	2	3	4	5	6	7
X ₁	a_A	1	1					
X ₂	b_A	X ₁₇						
X ₃	c_A	X ₁₈						
X ₄	d_A	X ₁₉						
X ₅	a_B	1						
X ₆	b_B	X ₂₀	1					
X ₇	c_B	X ₂₁						
X ₈	d_B	X ₂₂						
X ₉	a_O							
X ₁₀	b_O	X ₂₃						
X ₁₁	c_O	X ₂₄						
X ₁₂	d_O	X ₂₅						
X ₁₃	c _{ph1}	1						
X ₁₄	c _{ph2}	1						
X ₁₅	c _{ph3}	1						
X ₁₆	c _{ph4}	1						
X ₁₇	W _a A,b A	1	1	1	X ₂₆			
X ₁₈	W _b A,c A	1	1	1	X ₂₇			
X ₁₉	W _c A,d A	1	1	1	X ₂₈			
X ₂₀	W _a B,b B	1	1	1	X ₂₉			
X ₂₁	W _b B,c B	1	1	1	X ₃₀			
X ₂₂	W _c B,d B	1	1	1	X ₃₁			
X ₂₃	W _a O,b O	1	1					
X ₂₄	W _b O,c O	1	1					
X ₂₅	W _c O,d O	1	1					
X ₂₆	W _w _a O,b O, W _a A,b A	1	1	0	0	1		
X ₂₇	W _w _b O,c O, W _b A,c A	1	1	0	0	1		
X ₂₈	W _w _c O,d O, W _c A,d A	1	1	0	0	1		
X ₂₉	W _w _a O,b O, W _a B,b B	1	1	0	0	1		
X ₃₀	W _w _b O,c O, W _b B,c B	1	1	0	0	1		
X ₃₁	W _w _c O,d O, W _c B,d B	1	1	0	0	1		
X ₃₂	H _w _a A,b A	1	1	-0.1	1			
X ₃₃	H _w _b A,c A	1	1	-0.1	1			
X ₃₄	H _w _c A,d A	1	1	-0.1	1			
X ₃₅	H _w _a B,b B	1	1	-0.1	1			
X ₃₆	H _w _b B,c B	1	1	-0.1	1			
X ₃₇	H _w _c B,d B	1	1	-0.1	1			
X ₃₈	H _w _a O,b O	1						
X ₃₉	H _w _b O,c O	1						
X ₄₀	H _w _c O,d O	1						
X ₄₁	M _w _a A,b A	1	1	1	1	-1	-1	-1
X ₄₂	M _w _b A,c A	1	1	1	1	-1	-1	-1
X ₄₃	M _w _c A,d A	1	1	1	1	-1	-1	-1
X ₄₄	M _w _a B,b B	1	1	1	1	-1	-1	-1
X ₄₅	M _w _b B,c B	1	1	1	1	-1	-1	-1
X ₄₆	M _w _c B,d B	1	1	1	1	-1	-1	-1

Fig. 6.13 Role matrices for the connectivity: mcw for connection weights

mcfw	combination function weights	1 alogistic	2 steponce	3 max-hebb	4 smax
X ₁	a_A	1			
X ₂	b_A	1			
X ₃	c_A	1			
X ₄	d_A	1			
X ₅	a_B	1			
X ₆	b_B	1			
X ₇	c_B	1			
X ₈	d_B	1			
X ₉	a_O	1			
X ₁₀	b_O	1			
X ₁₁	c_O	1			
X ₁₂	d_O	1			
X ₁₃	c _{ph1}		1		
X ₁₄	c _{ph2}		1		
X ₁₅	c _{ph3}		1		
X ₁₆	c _{ph4}		1		
X ₁₇	W _{a A,b A}			1	
X ₁₈	W _{b A,c_A}			1	
X ₁₉	W _{c A,d A}			1	
X ₂₀	W _{a B,b B}			1	
X ₂₁	W _{b B,c B}			1	
X ₂₂	W _{c B,d B}			1	
X ₂₃	W _{a O,b_O}				1
X ₂₄	W _{b O,c_O}				1
X ₂₅	W _{c O,d_O}				1
X ₂₆	W _{w_{a O,b_O} w_{a A,b A}}			1	
X ₂₇	W _{w_{b O,c_O} w_{b A,c_A}}			1	
X ₂₈	W _{w_{c O,d_O} w_{c A,d A}}			1	
X ₂₉	W _{w_{a O,b_O} w_{a B,b B}}			1	
X ₃₀	W _{w_{b O,c_O} w_{b B,c B}}			1	
X ₃₁	W _{w_{c O,d_O} w_{c B,d B}}			1	
X ₃₂	H _{w_{a A,b_A}}	1			
X ₃₃	H _{w_{b A,c_A}}	1			
X ₃₄	H _{w_{c A,d_A}}	1			
X ₃₅	H _{w_{a B,b_B}}	1			
X ₃₆	H _{w_{b B,c_B}}	1			
X ₃₇	H _{w_{c B,d_B}}	1			
X ₃₈	H _{w_{a O,b_O}}	1			
X ₃₉	H _{w_{b O,c_O}}	1			
X ₄₀	H _{w_{c O,d_O}}	1			
X ₄₁	M _{w_{a A,b_A}}	1			
X ₄₂	M _{w_{b A,c_A}}	1			
X ₄₃	M _{w_{c A,d_A}}	1			
X ₄₄	M _{w_{a B,b_B}}	1			
X ₄₅	M _{w_{b B,c_B}}	1			
X ₄₆	M _{w_{c B,d_B}}	1			

Fig. 6.14 Role matrices for the aggregation characteristics: combination function weights

	mcfp	combination function parameters	1		2		3		4	
			alogistic		steponce		max-hebb		smax	
			1	2	1	2	1	2	1	2
			σ	τ	α	β	μ		λ	
X ₁	a_A		5	0.3						
X ₂	b_A		5	0.3						
X ₃	c_A		5	0.3						
X ₄	d_A		5	0.3						
X ₅	a_B		5	0.3						
X ₆	b_B		5	0.3						
X ₇	c_B		5	0.3						
X ₈	d_B		5	0.3						
X ₉	a_O		5	0.3						
X ₁₀	b_O		5	0.3						
X ₁₁	c_O		5	0.3						
X ₁₂	d_O		5	0.3						
X ₁₃	c _{ph1}				20	300				
X ₁₄	c _{ph2}				350	400				
X ₁₅	c _{ph3}				450	600				
X ₁₆	c _{ph4}				650	850				
X ₁₇	W _{a A,b A}						X ₄₁			
X ₁₈	W _{b A,c A}						X ₄₂			
X ₁₉	W _{c A,d A}						X ₄₃			
X ₂₀	W _{a B,b B}						X ₄₄			
X ₂₁	W _{b B,c B}						X ₄₅			
X ₂₂	W _{c B,d B}						X ₄₆			
X ₂₃	W _{a O,b O}								1	
X ₂₄	W _{b O,c O}								1	
X ₂₅	W _{c O,d O}								1	
X ₂₆	W _{w_a O,b O, w_a A,b A}								1	
X ₂₇	W _{w_b O,c O, w_b A,c A}								1	
X ₂₈	W _{w_c O,d O, w_c A,d A}								1	
X ₂₉	W _{w_a O,b O, w_a B,b B}								1	
X ₃₀	W _{w_b O,c O, w_b B,c B}								1	
X ₃₁	W _{w_c O,d O, w_c B,d B}								1	
X ₃₂	H _{w_a A,b A}		5	0.3						
X ₃₃	H _{w_b A,c A}		5	0.3						
X ₃₄	H _{w_c A,d A}		5	0.3						
X ₃₅	H _{w_a B,b B}		5	0.3						
X ₃₆	H _{w_b B,c B}		5	0.3						
X ₃₇	H _{w_c B,d B}		5	0.3						
X ₃₈	H _{w_a O,b O}		5	0.3						
X ₃₉	H _{w_b O,c O}		5	0.3						
X ₄₀	H _{w_c O,d O}		5	0.3						
X ₄₁	M _{w_a A,b A}		5	2						
X ₄₂	M _{w_b A,c A}		5	2						
X ₄₃	M _{w_c A,d A}		5	2						
X ₄₄	M _{w_a B,b B}		5	2						
X ₄₅	M _{w_b B,c B}		5	2						
X ₄₆	M _{w_c B,d B}		5	2						

Fig. 6.15 Role matrices for the aggregation characteristics: combination function parameters

ms	speed factors	1
X ₁	a_A	1
X ₂	b_A	1
X ₃	c_A	1
X ₄	d_A	1
X ₅	a_B	1
X ₆	b_B	1
X ₇	c_B	1
X ₈	d_B	1
X ₉	a_O	1
X ₁₀	b_O	1
X ₁₁	c_O	1
X ₁₂	d_O	1
X ₁₃	C _{ph1}	1
X ₁₄	C _{ph2}	1
X ₁₅	C _{ph3}	1
X ₁₆	C _{ph4}	1
X ₁₇	W _a A,b A	X ₃₂
X ₁₈	W _b A,c A	X ₃₃
X ₁₉	W _c A,d A	X ₃₄
X ₂₀	W _a B,b B	X ₃₅
X ₂₁	W _b B,c B	X ₃₆
X ₂₂	W _c B,d B	X ₃₇
X ₂₃	W _a O,b O	X ₃₈
X ₂₄	W _b O,c O	X ₃₉
X ₂₅	W _c O,d O	X ₄₀
X ₂₆	W _w a O,b O, W _a A,b A	0.2
X ₂₇	W _w b O,c O, W _b A,c A	0.2
X ₂₈	W _w c O,d O, W _c A,d A	0.2
X ₂₉	W _w a O,b O, W _a B,b B	0.2
X ₃₀	W _w b O,c O, W _b B,c B	0.2
X ₃₁	W _w c O,d O, W _c B,d B	0.2
X ₃₂	H _w a A,b A	0
X ₃₃	H _w b A,c A	0
X ₃₄	H _w c A,d A	0
X ₃₅	H _w a B,b B	0
X ₃₆	H _w b B,c B	0
X ₃₇	H _w c B,d B	0
X ₃₈	H _w a O,b O	0.9
X ₃₉	H _w b O,c O	0.9
X ₄₀	H _w c O,d O	0.9
X ₄₁	M _w a A,b A	0
X ₄₂	M _w b A,c A	0
X ₄₃	M _w c A,d A	0
X ₄₄	M _w a B,b B	0
X ₄₅	M _w b B,c B	0
X ₄₆	M _w c B,d B	0

iv	initial values	1
X ₁	a_A	0
X ₂	b_A	0
X ₃	c_A	0
X ₄	d_A	0
X ₅	a_B	0
X ₆	b_B	0
X ₇	c_B	0
X ₈	d_B	0
X ₉	a_O	0
X ₁₀	b_O	0
X ₁₁	c_O	0
X ₁₂	d_O	0
X ₁₃	C _{ph1}	0
X ₁₄	C _{ph2}	0
X ₁₅	C _{ph3}	0
X ₁₆	C _{ph4}	0
X ₁₇	W _a A,b A	0.1
X ₁₈	W _b A,c A	0.1
X ₁₉	W _c A,d A	0
X ₂₀	W _a B,b B	0
X ₂₁	W _b B,c B	0.1
X ₂₂	W _c B,d B	0.1
X ₂₃	W _a O,b O	0
X ₂₄	W _b O,c O	0
X ₂₅	W _c O,d O	0
X ₂₆	W _w a O,b O, W _a A,b A	0
X ₂₇	W _w b O,c O, W _b A,c A	0
X ₂₈	W _w c O,d O, W _c A,d A	0
X ₂₉	W _w a O,b O, W _a B,b B	0
X ₃₀	W _w b O,c O, W _b B,c B	0
X ₃₁	W _w c O,d O, W _c B,d B	0
X ₃₂	H _w a A,b A	0.05
X ₃₃	H _w b A,c A	0.05
X ₃₄	H _w c A,d A	0.05
X ₃₅	H _w a B,b B	0.05
X ₃₆	H _w b B,c B	0.05
X ₃₇	H _w c B,d B	0.05
X ₃₈	H _w a O,b O	0
X ₃₉	H _w b O,c O	0
X ₄₀	H _w c O,d O	0
X ₄₁	M _w a A,b A	0.995
X ₄₂	M _w b A,c A	0.995
X ₄₃	M _w c A,d A	0.995
X ₄₄	M _w a B,b B	0.99
X ₄₅	M _w b B,c B	0.99
X ₄₆	M _w c B,d B	0.99

Fig. 6.16 Role matrices **ms** for the timing characteristics (speed factors) and initial values **iv**

6.8.2 Role Matrices for Aggregation Characteristics

The network characteristics for aggregation are defined by the selection of combination functions from the library and values for their parameters. In role matrix **mcfw** it is specified by weights which state uses which combination function; see Fig. 6.14.

In role matrix **mcfp** (see Fig. 6.15) it is indicated what the parameter values are for the chosen combination functions. Some of them are adaptive, as can be seen in the rows from X_{17} to X_{22} (e.g., the persistence factors μ represented by the self-model states X_{41} to X_{46}).

6.8.3 Role Matrices for Timing Characteristics

In Fig. 6.16, the role matrix **ms** for speed factors is shown, which lists all speed factors. Next to it, the list of initial values can be found. Also for **ms** some entries are adaptive: the speed factors of X_{17} to X_{25} are represented by (second-order) self-model states X_{32} to X_{40} .

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