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Computational modeling of organisational learning by self-modeling networks

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ABSTRACT

Within organisational learning literature, mental models are considered a vehicle for both individual learning and organizational learning. By learning individual mental models (and making them explicit), a basis for formation of shared mental models for the level of the organization is created, which after its formation can then be adopted by individuals. This provides mechanisms for organizational 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.

1. Introduction

Learning is an essential part of survival, and has been a topic intensively studied. Organizational 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 the organization is different from that of all the individuals in the organization, and it is non-linear because it has feedback mechanisms which provide individuals to learn from the organization. The concept of organizational learning has been addressed, for example, in (Argyris & Schön, 1978; Bogenrieder, 2002; Crossan, Lane, & White, 1999; Fischhof & Johnson, 1997; Kim, 1993; McShane & von Glinow, 2010; Stelmaszczyk, 2016; Wiewiora, Smidt, & Chang, 2019). However, the extensive literature on the concept of organizational learning has some deficiencies when it comes to computational models for it. There seems to be no detailed computational formalization of a clearly defined organizational learning process from beginning to end. In this study, a self-modeling network perspective is used to model the different processes and phases of organizational learning.

The transitions between individual and organizational learning are keypoints of understanding and directing the learning process of organizations (Kim, 1993). Without any doubt, one of the most influential papers on organisational learning is (Kim, 1993) with an impressive number of 4696 citations in Google Scholar by now (dd. August 19, 2021). The following quote illustrates in a summarized form the perspective sketched by Kim (1993):

> ‘Organizational 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 organizational 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 organization’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 the 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 organizational learning and its processes and phases. Computational modeling of organizational 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, 2020b) that will be explained in detail in Section 3 was used in this current paper.

First, Section 2 presents how and in what aspects literature provides ideas on mental models and their role in organizational learning. Then, Section 3 explains the characteristics and details of adaptive self-

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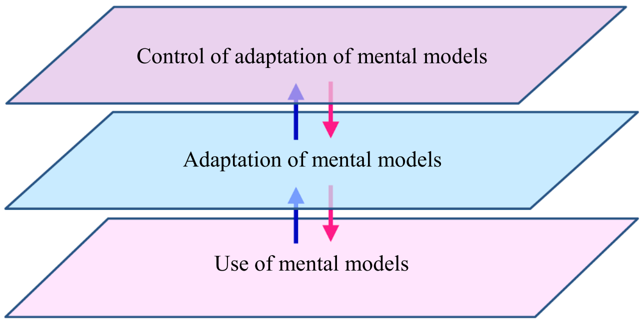

Fig. 1. Cognitive architecture for mental model handling with three levels of mental processing for mental models.

modeling network models and how they can be used to model the different processes concerning dynamics, adaptation and control of mental models. In Section 4 the controlled adaptive network model for organisational learning is introduced. Then in Section 5, an example simulation scenario is explained in detail. In Section 6 equilibrium analysis of the introduced adaptive network model is provided. Section 7 is a Discussion section. Lastly, Section 8 is an appendix with a full specification of the model.

2. Background literature

The topic addressed in this paper 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 Section 4 and accordingly for the scientific justification of the model based on this multidisciplinary literature.

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. For some more references on mental models, see (Doyle and Ford, 1998; Gentner and Stevens, 1983; Johnson-Laird, 1983).

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

Specific forms of learning that can be applied to mental models are observational learning (Van Gog, Paas, Marcus, Ayres, & Sweller, 2009; Yi & Davis, 2003), instructional learning (Hogan & Pressley, 1997) and combinations thereof.

By using the notion of self-modeling network (or reified network) from (Treur, 2020a, 2020b), 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 & Van Ments, 2022); see also Section 3.

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 (Fischhof & Johnson, 1997; Jones & Roelofsma, 2000; Mathieu, Hefner, Goodwin, Salas, & Cannon-Bowers, 2000; Burthscher, Kolbe, & Wacker, 2011; Wilson, 2019; Todd, 2018). This has major implications for health care and patent 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 (Krueger, 1998; Ross, Greene, & House, 1977) 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, Kunreuther, & Schoemaker, 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., (Isenberg, 1986; Lamm & Myers, 1978). 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

Table 1
The combination functions used in the introduced network model.

	Notation	Formula	Parameters
Advanced logistic sum	$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$	$\left[\frac{1}{1+e^{-\sigma(V_1+\ldots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau})}\right](1+e^{-\sigma\tau})$	Steepness $\sigma > 0$ Excitability threshold τ
Steponce	$\mathbf{steponce}_{\alpha,\beta}(..)$	1 if time t is between α and β, else 0	Start time α End time β
Hebbian learning	$\mathbf{hebb}_{\mu}(V_1, V_2, V_3)$	$V_1{*}V_2(1 - V_3) + \mu V_3$	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	$\mathbf{max\text{-}hebb}_{\mu}(V_1, \ldots, V_k)$	$\max(\mathbf{hebb}_{\mu}(V_1, V_2, V_3), V_4, \ldots, V_k)$	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	$\mathbf{smax}_{\lambda}(V_1, \ldots, V_k)$	$\max(V_1, \ldots, V_k)/\lambda$	Scaling factor λ

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, Giuliano, & Appelman, 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 that which a rational.

An example of a computational model of a shared mental model and how imperfections in it work out can be found in (Van Ments, Treur, Klein, Roelofsma, 2021). The model also uses the cognitive architecture for mental models depicted in Fig. 1 and its computational formalization addressed in (Treur & Van Ments, 2022). For some more references on shared mental models, see (DeChurch and Mesmer-Magnus, 2010; Dionne, Sayama, Hao, Bush, 2010; Langan-Fox, Code, Langfield-Smith, 2000; Nini, 2019)

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 & Schön, 1978; Bogenrieder, 2002; Crossan et al., 1999; Fischhof & Johnson, 1997; Kim, 1993; McShane & von Glinow, 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 in the perspective sketched by Kim (1993). Here, mental models are considered a vehicle for both individual learning and organizational learning. By learning individual mental models (and making them explicit), a basis for formation of shared mental models for the level of the organization is created, which provides a mechanism for organizational learning. Inspired by this, the overall process consists of the following main processes and interactions, see also (Kim, 1993)

(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 organization level**
  (1) Deciding about creation of shared mental models
  (2) Creating shared mental models based on developed individual mental models
(c) **Organization 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 organization 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. 1, applying a chosen individual mental model for internal simulation relates to the base level, learning or 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 organization level and vice versa involve changing (individual or shared) mental models and therefore relate to the middle level, while the decision 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 organizational learning that will be introduced in Section 4.

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 $\boldsymbol{\omega}_{X,Y}$
- *Aggregation characteristics*
  For any state Y, some combination function $\mathbf{c}_Y(..)$ defines the aggregation that is applied to the impacts $\boldsymbol{\omega}_{X,Y}X(t)$ on Y from its incoming connections from states X
- *Timing characteristics*
  Each state Y has a speed factor $\boldsymbol{\eta}_Y$ 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 $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\boldsymbol{\eta}_Y$ in a standard numerical format:

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

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 50 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 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, 2020b). 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 Section 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 $\boldsymbol{\omega}_{X,Y}$ 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 $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\boldsymbol{\eta}_Y$ can be made adaptive by including self-model states for them. For example, an adaptive speed factor $\boldsymbol{\eta}_Y$ 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 $\boldsymbol{\eta}_{\mathbf{W}_{X,Y}}$ for the dynamics of first-order self-model state $\mathbf{W}_{X,Y}$ which in turn represents the adaptation of connection weight $\boldsymbol{\omega}_{X,Y}$. Similarly, a persistence factor $\boldsymbol{\mu}_{\mathbf{W}_{X,Y}}$ of such a first-order self-model state $\mathbf{W}_{X,Y}$ used for adaptation (e.g., based on Hebbian learning (Hebb, 1949)) can be represented by a second-order self-model state $\mathbf{M}_{\mathbf{W}_{X,Y}}$. Such second-order self-model states can be used to control adaptation.

In the current paper, 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 organizational learning by proper handling of individual mental models and shared mental models. In this self-modeling network 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. 2. In this way the three-level cognitive architecture depicted in Fig. 1 is formalized computationally in the form of a self-modeling network architecture .

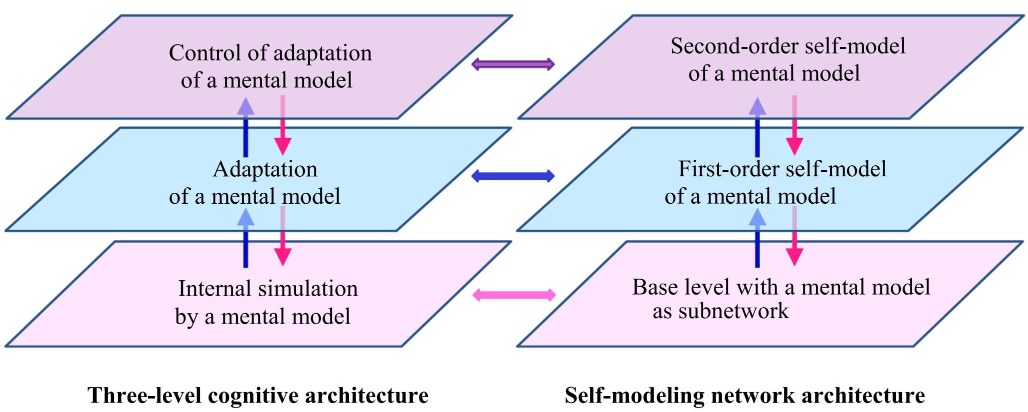

Fig. 2. Computational formalization of the three-level cognitive architecture for mental model handling from Fig. 1 by a self-modeling network architecture.

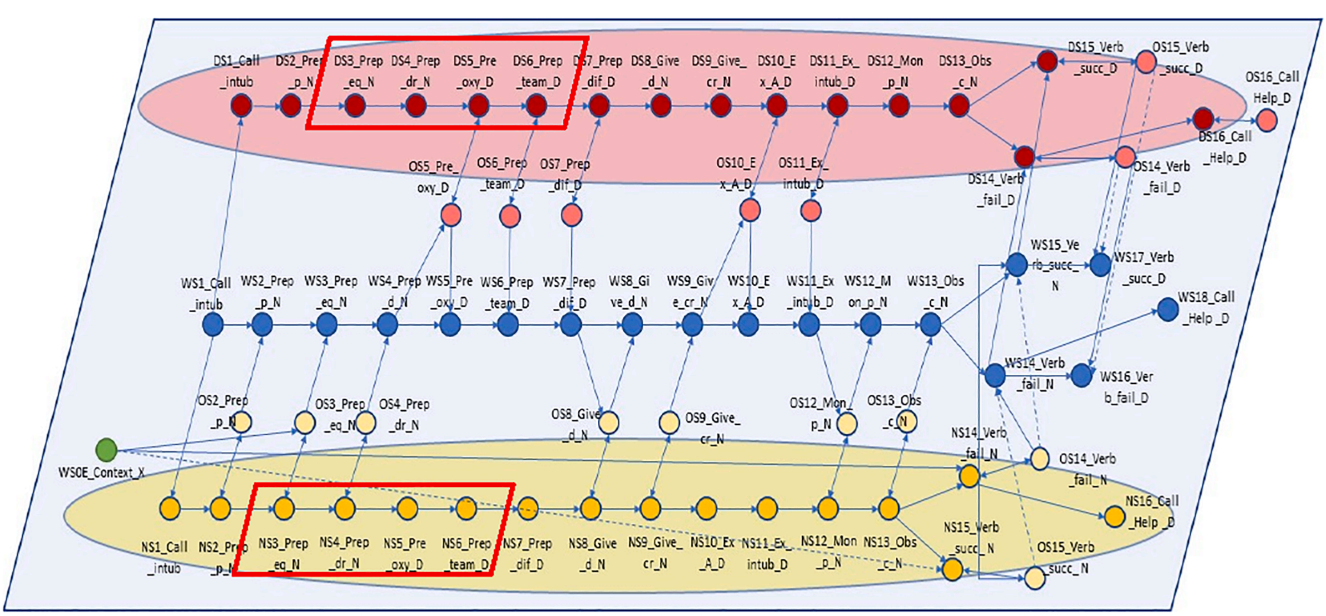

Fig. 3. The example mental model from (Van Ments et al, 2021a, 2021b) with indicated the part used in the current paper.

Table 2
The mental model used for the simple case study.

States for mental models of persons A, B and organization 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

In Bhalwankar and Treur (2021a, 2021b) 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 & Davis, 2003; Van Gog et al., 2009) and instructional learning (Hogan & Pressley, 1997) and combinations thereof. Such forms of learning will also be applied in the model for organizational learning introduced here in Section 4.

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, 2021b). Here only the part of the mental models is used that addresses four mental states; see the red outlined parts in Figur.e 3 and the explanations in Table 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 organizational learning addressed to improve the situation covers:

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 (Hebb, 1949). 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 organization mental model based on the two individual mental models. A process of unification by aggregation takes place.
3. Learning individual mental models from the shared mental model; e.g., a form of instructional learning.

Table 3
Base level states of the introduced adaptive network model.

Nr	State	Explanation
X_1	a_A	Individual mental model state for person A for task a
X_2	b_A	Individual mental model state for person A for task b
X_3	c_A	Individual mental model state for person A for task c
X_4	d_A	Individual mental model state for person A for task d
X_5	a_B	Individual mental model state for person B for task a
X_6	b_B	Individual mental model state for person B for task b
X_7	c_B	Individual mental model state for person B for task c
X_8	d_B	Individual mental model state for person B for task d
X_9	a_O	Shared mental model state for organization O for task a
X_{10}	b_O	Shared mental model state for organization O for task b
X_{11}	c_O	Shared mental model state for organization O for task c
X_{12}	d_O	Shared mental model state for organization O for task d
X_{13}	con_{ph1}	Context state for Phase 1: individual mental model simulation and learning
X_{14}	con_{ph2}	Context state for Phase 2: creation of a shared mental model for organization O
X_{15}	con_{ph3}	Context state for Phase 3: learning individual mental models from the shared mental model for organization O
X_{16}	con_{ph4}	Context state for Phase 4: individual mental model simulation and learning

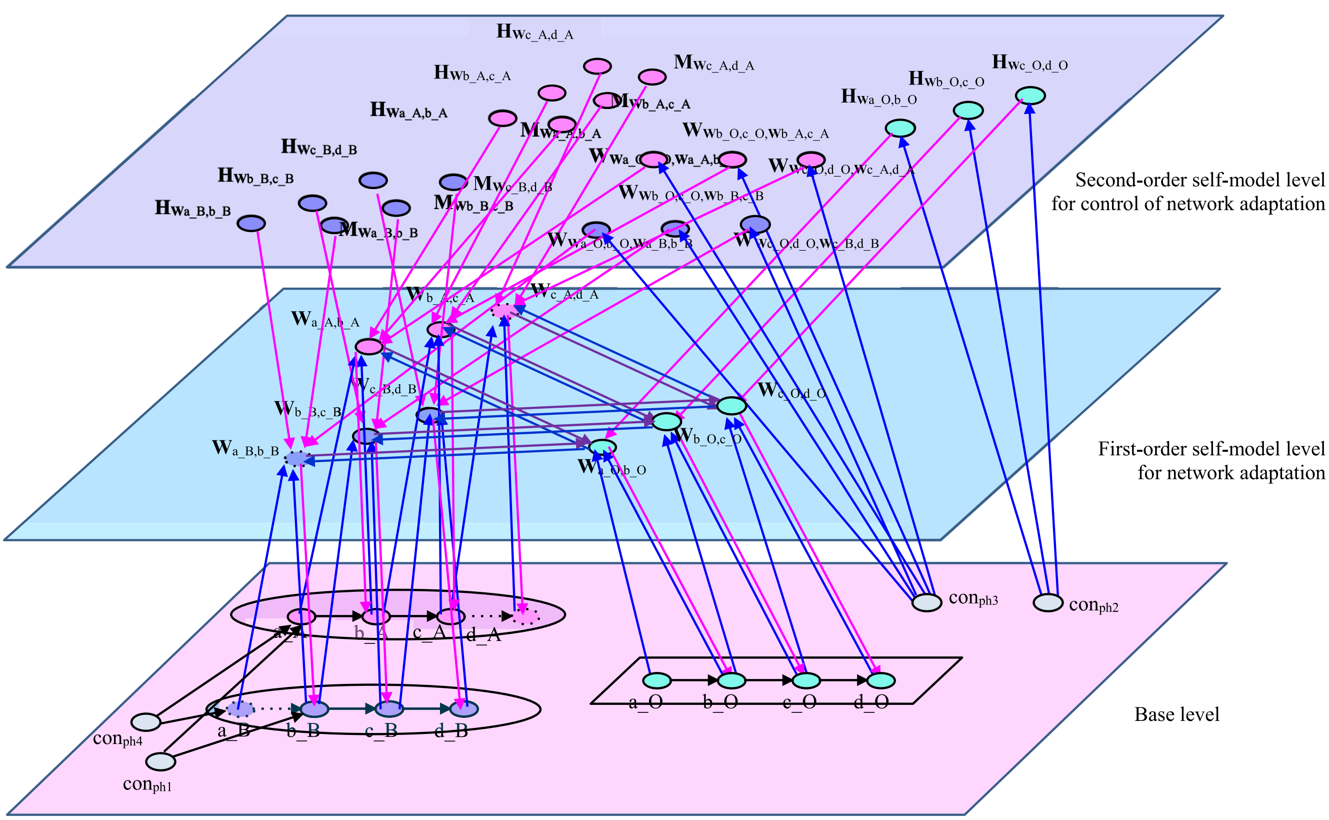

Fig. 4. The connectivity of the second-order adaptive network model.

Table 4
First-order self-model states of the introduced adaptive network model.

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

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. 4; for an overview of the states, see Table 3 to 5. For more details about the connections and how they relate to (a) to (d) from Section 2.3, see Table 6.

In this model, at the base level individual mental states of persons and shared mental model states of the organization 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 organization'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 weight of a connection between the same tasks for all people (two for this case) to the **W**-states representing the weights of the connections of the shared organization model (for the formation of the shared organization mental model) and vice versa (for the learning of the shared organization mental model by the individuals). At the second-order self-model level, there are higher-order **W**-states specifying the weights of the connections from the **W**-states to the individual ones (to initiate and control the learning of the shared organization mental model by the individuals), $\mathbf{H}_\mathbf{W}$-states for adaptation speeds of connection weights in the first-order adaptation level, and $\mathbf{M}_\mathbf{W}$-states for persistence of adaptation. This provides the speed and persistence control of the adaptation.

Table 5
Second-order self-model states of the introduced adaptive network model.

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 $\mathbf{W}_{c\_B,d\_B}$

Table 6
Types of connections in the adaptive network model and how they relate to **(a)** to **(d)** identified in Section 2.3. For the example scenario, *x* and *y* are states from {a, b, c, d} and *Z* is a person from {A, B}.

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 organization O: **(a)** from Sect. 2.3.	
$\mathrm{con}_p \rightarrow x\_Z$	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.	
$\mathbf{W}_{x\_Z,y\_Z} \rightarrow \mathbf{W}_{x\_O,y\_O}$	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.	
$\mathbf{W}_{x\_O,y\_O} \rightarrow \mathbf{W}_{x\_Z,y\_Z}$	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.	
$\mathbf{W}_{x\_Z,y\_Z} \rightarrow \mathbf{W}_{x\_Z,y\_Z}$	Persistence connection for *Z*'s mental model connections: **(a)** from Sect. 2.3.	
Interlevel connections		
$x\_Z \rightarrow \mathbf{W}_{x\_Z,y\_Z}$	Connection for individual Hebbian learning from state *x* in person *Z*'s individual mental model to self-model state $\mathbf{W}_{x\_A,y\_A}$ for *Z*'s individual mental model: **(a)** from Sect. 2.3.	Upward from base level to first self-model level
$y\_Z \rightarrow \mathbf{W}_{x\_Z,y\_Z}$	Connection for individual Hebbian learning from state *y* in person *Z*'s individual mental model to self-model state $\mathbf{W}_{x\_A,y\_A}$ for *Z*'s individual mental model: **(a)** from Sect. 2.3.	
$x\_O \rightarrow \mathbf{W}_{x\_O,y\_O}$	Connection for Hebbian learning from state *x* in O's shared mental model to self-model state $\mathbf{W}_{x\_A,y\_A}$ for O's shared mental model: **(c)** from Sect. 2.3.	
$y\_O \rightarrow \mathbf{W}_{x\_O,y\_O}$	Connection for Hebbian learning from state *y* in O's shared mental model to self-model state $\mathbf{W}_{x\_A,y\_A}$ for O's shared mental model: **(c)** from Sect. 2.3.	
$\mathbf{W}_{x\_Z,y\_Z} \rightarrow y\_Z$	Connection for the effect of self-model state $\mathbf{W}_{x\_Z,y\_Z}$ 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
$\mathbf{W}_{x\_O,y\_O} \rightarrow y\_O$	Connection for the effect of self-model state $\mathbf{W}_{x\_O,y\_O}$ for O's shared mental model on state *y* in O's shared mental model: **(c)** from Sect. 2.3.	
$\mathrm{con}_{ph2} \rightarrow \mathbf{H}_{\mathbf{W}_{x\_O,y\_O}}$	Connection from the context state for Phase 2 to second-order self-model state $\mathbf{H}_{\mathbf{W}_{a\_O,b\_O}}$ representing the adaptation speed of first-order self-model state $\mathbf{W}_{x\_O,y\_O}$ 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
$\mathrm{con}_{ph3} \rightarrow \mathbf{W}_{\mathbf{W}_{x\_O,y\_O},\mathbf{W}_{x\_Z,y\_Z}}$	Connection from the context state for Phase 3 to second-order self-model state $\mathbf{W}_{\mathbf{W}_{x\_O,y\_O},\mathbf{W}_{x\_Z,y\_Z}}$ representing the weight of the connection from first-order self-model state $\mathbf{W}_{x\_O,y\_O}$ for the weight of the connection from *x* to *y* in the shared mental model of O to first-order self-model state $\mathbf{W}_{x\_Z,y\_Z}$ 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.	
$\mathbf{H}_{\mathbf{W}_{x\_O,y\_O}} \rightarrow \mathbf{W}_{x\_O,y\_O}$	Effectuation of control of the adaptation of O's shared mental model connection weight $\mathbf{W}_{x\_O,y\_O}$ for shared mental model formation based on *Z*'s individual mental model: **(b)**, **(c)** from Sect. 2.3.	Downward from second- to first-order self-model level
$\mathbf{W}_{\mathbf{W}_{x\_O,y\_O},\mathbf{W}_{x\_Z,y\_Z}} \rightarrow \mathbf{W}_{x\_Z,y\_Z}$	Effectuation of control of the adaptation of person *Z*'s individual mental model connection weight $\mathbf{W}_{x\_Z,y\_Z}$ for instructional learning of *Z*'s individual mental model from O's shared mental model: **(d)** from Sect. 2.3.	

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 organization then. Thus, it is possible to explore how organizational 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 Section 2.3. Two distinct mental models representing two different employees in the same group or organization 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 organization. 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 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 Section 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 organizational 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 organization.

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

This relates to **(d)** in Section 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 by the individuals 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**

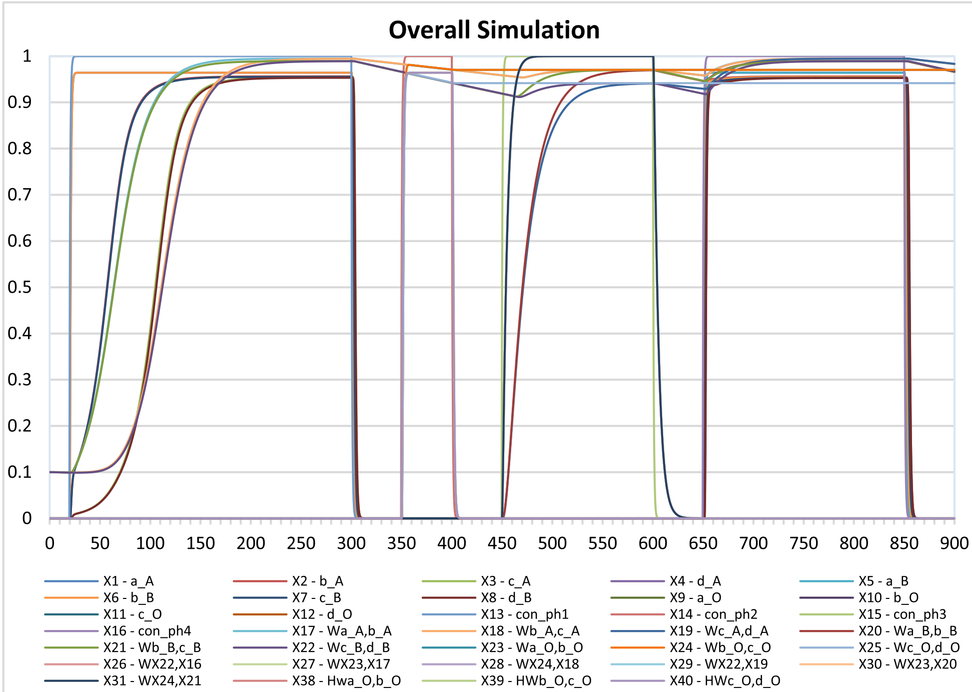

Fig. 5. Simulation graph showing all states.

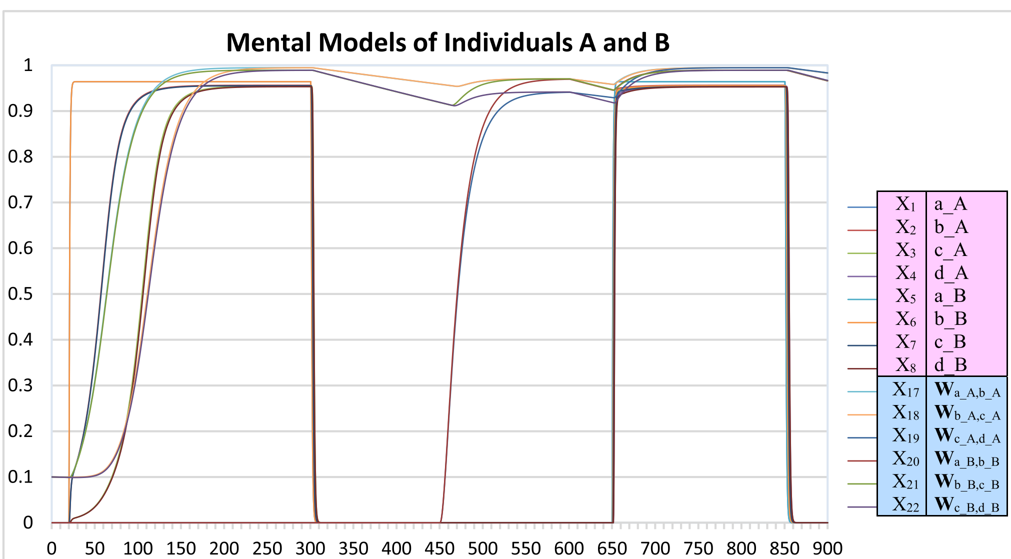

Fig. 6. The base states and connection weight self-model states for the individual mental models.

This relates to **(d)** in Section 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 organizational learning.

Fig. 5 shows an overview of all states of the simulation; Fig. 6 and Fig. 7 focus on part of the states (for the same simulation) to get a more detailed view.

In Fig. 6 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

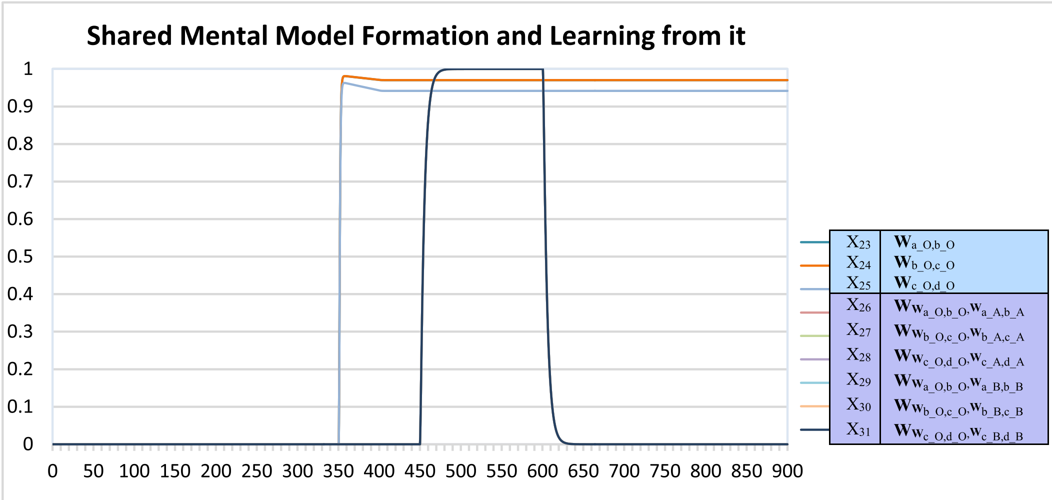

Fig. 7. The connection weight self-model states for the shared mental model and the weights by which individuals receive instructional learning of the shared mental model.

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 $\mathbf{W}_{a\_A,b\_A}$ and $\mathbf{W}_{b\_A,c\_A}$ 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 connections $\mathbf{W}_{b\_B,c\_B}$ and $\mathbf{W}_{c\_B,d\_B}$ 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} ($\mathbf{W}_{c\_A,d\_A}$) 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 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 paper, organizational learning. As will be explained in more detail in the following paragraph, the **W**-states of the organization'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. 7, 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 that specify the model (see Section 8), 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. 7, states X_{23}, X_{24} and X_{25} (shared mental model connection weight self-model states $\mathbf{W}_{a\_O,b\_O}$, $\mathbf{W}_{b\_O,c\_O}$, and $\mathbf{W}_{c\_O,d\_O}$) 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. Mathematical analysis of equilibria of the network model

In general, a dynamical system is in equilibrium at time t if $\mathrm{d}Y(t)/\mathrm{d}t = 0$ for all of its state variables Y. The same can be applied to self-modeling network models. However, given the standard equation (1) in terms of the network characteristics, for network models the condition $\mathrm{d}Y(t)/\mathrm{d}t = 0$ can be formulated in terms of the network characteristics as the following simple criterion

$$\boldsymbol{\eta}_Y = 0 \;\; or \;\; \mathbf{c}_Y\left(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t)\right) = Y(t) \tag{2}$$

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 1.

$$\mathbf{max} - \mathbf{hebb}_{\boldsymbol{\mu}}(V_1, \ldots, V_k) = \mathbf{max}\left(\mathbf{hebb}_{\boldsymbol{\mu}}(V_1, V_2, V_3), V_4, \ldots, V_k\right) \tag{3}$$

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

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

$$\boldsymbol{\eta}_Y = 0 \;\; or \;\; \max(V_1 * V_2(1 - V_3) + \boldsymbol{\mu} V_3, V_4, \ldots, V_k) = Y(t) \tag{4}$$

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 $\mathbf{W}_{\mathbf{W}_{b\_O,c\_O},\mathbf{W}_{b\_A,c\_A}}$ which is X_{27}). Moreover, $\boldsymbol{\mu} = 0.995$. From the simulation results it seems that this state is (approximately) stationary at time $t = 299$ and at time $t = 849$. The speed factor $\boldsymbol{\eta}$ 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:

$V_1 = X_2(299) = 0.956268089647092$
$V_2 = X_3(299) = 0.954552603376293$
$V_3 = X_{18}(299) = 0.994443719684304$
$V_4 = X_{24}(299) = 0$
$\boldsymbol{\mu} = 0.995$

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

$\max(V_1 * V_2(1 - V_3) + \boldsymbol{\mu} V_3, V_4, \ldots, V_k) = 0.994543319288979$
$Y(299) = 0.994443719684304$

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 $t = 849$:

$V_1 = X_2(849) = 0.956269533716948$
$V_2 = X_3(849) = 0.95457581935179$
$V_3 = X_{18}(849) = 0.994548119402481$
$V_4 = X_{24}(849) = 0.970297110356546$
$\boldsymbol{\mu} = 0.995$

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

$\max(V_1 {*} V_2(1 - V_3) + \boldsymbol{\mu} V_3, V_4, \ldots, V_k) = 0.994552028641134$
$Y(849) = 0.994548119402481$

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.

7. Discussion

Organisational learning is a complex process that is challenging when computation modeling of it is concerned; computational models of organizational 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 organizational learning. By learning individual mental models, sources for the formation of shared mental models for the level of the organization as a whole are created. Once these shared organization mental models have been formed, they are available to be adopted by individuals within the organization 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 organizational 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 organizational 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 & 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 & Treur, 2021). Another context for adaptation is for Hebbian learning (Hebb, 1949) as applied during internal mental simulation in (Canbaloğlu & Treur, 2021) and in (Bhalwankar & Treur, 2021a,b) during observational learning. These different types of adaptation were also adopted in the adaptive network for organizational learning introduced in the current paper. Thereby, the context-sensitive control of them was modeled by the second-order self-model level.

For this first step in computational formalization of organizational 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 & Treur, 2021a,b).

Finally, yet another option for an extension is to add an intermediate level of teams in between the individual and organizational level as, for example, discussed in (Wiewiora et al., 2019). In the forthcoming book on computational modeling of multilevel organisational learning (Canbaloğlu, Treur, & Wiewiora, forthcoming), most of the abovementioned issues (and a few more) will be covered by extensions, variations, and refinements of the adaptive network model introduced in the current paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Full specification by role matrices

In Figs. 8 to 12 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.

A.1. Role matrices for connectivity characteristics

The connectivity characteristics are specified by role matrices **mb** and **mcw** shown in Fig. 8 and Fig. 9. 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. 9) 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 connectivity	1	2	3	4	5	6	7
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}	$\mathbf{W}_{a\_A,b\_A}$	X_1	X_2	X_{17}	X_{23}			
X_{18}	$\mathbf{W}_{b\_A,c\_A}$	X_2	X_3	X_{18}	X_{24}			
X_{19}	$\mathbf{W}_{c\_A,d\_A}$	X_3	X_4	X_{19}	X_{25}			
X_{20}	$\mathbf{W}_{a\_B,b\_B}$	X_5	X_6	X_{20}	X_{23}			
X_{21}	$\mathbf{W}_{b\_B,c\_B}$	X_6	X_7	X_{21}	X_{24}			
X_{22}	$\mathbf{W}_{c\_B,d\_B}$	X_7	X_8	X_{22}	X_{25}			
X_{23}	$\mathbf{W}_{a\_O,b\_O}$	X_{17}	X_{20}					
X_{24}	$\mathbf{W}_{b\_O,c\_O}$	X_{18}	X_{21}					
X_{25}	$\mathbf{W}_{c\_O,d\_O}$	X_{19}	X_{22}					
X_{26}	$\mathbf{Ww}_{a\_O,b\_O,\mathbf{w}_{a\_A,b\_A}}$	X_{23}	X_{17}	X_{13}	X_{14}	X_{15}		
X_{27}	$\mathbf{Ww}_{b\_O,c\_O,\mathbf{w}_{b\_A,c\_A}}$	X_{24}	X_{18}	X_{13}	X_{14}	X_{15}		
X_{28}	$\mathbf{Ww}_{c\_O,d\_O,\mathbf{w}_{c\_A,d\_A}}$	X_{25}	X_{19}	X_{13}	X_{14}	X_{15}		
X_{29}	$\mathbf{Ww}_{a\_O,b\_O,\mathbf{w}_{a\_B,b\_B}}$	X_{23}	X_{20}	X_{13}	X_{14}	X_{15}		
X_{30}	$\mathbf{Ww}_{b\_O,c\_O,\mathbf{w}_{b\_B,c\_B}}$	X_{24}	X_{21}	X_{13}	X_{14}	X_{15}		
X_{31}	$\mathbf{Ww}_{c\_O,d\_O,\mathbf{w}_{c\_B,d\_B}}$	X_{25}	X_{22}	X_{13}	X_{14}	X_{15}		
X_{32}	$\mathbf{Hw}_{a\_A,b\_A}$	X_1	X_2	X_{17}	X_{32}			
X_{33}	$\mathbf{Hw}_{b\_A,c\_A}$	X_2	X_3	X_{18}	X_{33}			
X_{34}	$\mathbf{Hw}_{c\_A,d\_A}$	X_3	X_4	X_{19}	X_{34}			
X_{35}	$\mathbf{Hw}_{a\_B,b\_B}$	X_5	X_6	X_{20}	X_{35}			
X_{36}	$\mathbf{Hw}_{b\_B,c\_B}$	X_6	X_7	X_{21}	X_{36}			
X_{37}	$\mathbf{Hw}_{c\_B,d\_B}$	X_7	X_8	X_{22}	X_{37}			
X_{38}	$\mathbf{Hw}_{a\_O,b\_O}$	X_{14}						
X_{39}	$\mathbf{Hw}_{b\_O,c\_O}$	X_{14}						
X_{40}	$\mathbf{Hw}_{c\_O,d\_O}$	X_{14}						
X_{41}	$\mathbf{Mw}_{a\_A,b\_A}$	X_1	X_2	X_{17}	X_{41}	X_{13}	X_{14}	X_{15}
X_{42}	$\mathbf{Mw}_{b\_A,c\_A}$	X_2	X_3	X_{18}	X_{42}	X_{13}	X_{14}	X_{15}
X_{43}	$\mathbf{Mw}_{c\_A,d\_A}$	X_3	X_4	X_{19}	X_{43}	X_{13}	X_{14}	X_{15}
X_{44}	$\mathbf{Mw}_{a\_B,b\_B}$	X_5	X_6	X_{20}	X_{44}	X_{13}	X_{14}	X_{15}
X_{45}	$\mathbf{Mw}_{b\_B,c\_B}$	X_6	X_7	X_{21}	X_{45}	X_{13}	X_{14}	X_{15}
X_{46}	$\mathbf{Mw}_{c\_B,d\_B}$	X_7	X_8	X_{22}	X_{46}	X_{13}	X_{14}	X_{15}

Fig. 8. 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}	$\mathbf{W}_{a\_A,b\_A}$	1	1	1	X_{26}			
X_{18}	$\mathbf{W}_{b\_A,c\_A}$	1	1	1	X_{27}			
X_{19}	$\mathbf{W}_{c\_A,d\_A}$	1	1	1	X_{28}			
X_{20}	$\mathbf{W}_{a\_B,b\_B}$	1	1	1	X_{29}			
X_{21}	$\mathbf{W}_{b\_B,c\_B}$	1	1	1	X_{30}			
X_{22}	$\mathbf{W}_{c\_B,d\_B}$	1	1	1	X_{31}			
X_{23}	$\mathbf{W}_{a\_O,b\_O}$	1	1					
X_{24}	$\mathbf{W}_{b\_O,c\_O}$	1	1					
X_{25}	$\mathbf{W}_{c\_O,d\_O}$	1	1					
X_{26}	$\mathbf{Ww}_{a\_O,b\_O,\mathbf{w}_{a\_A,b\_A}}$	1	1	0	0	1		
X_{27}	$\mathbf{Ww}_{b\_O,c\_O,\mathbf{w}_{b\_A,c\_A}}$	1	1	0	0	1		
X_{28}	$\mathbf{Ww}_{c\_O,d\_O,\mathbf{w}_{c\_A,d\_A}}$	1	1	0	0	1		
X_{29}	$\mathbf{Ww}_{a\_O,b\_O,\mathbf{w}_{a\_B,b\_B}}$	1	1	0	0	1		
X_{30}	$\mathbf{Ww}_{b\_O,c\_O,\mathbf{w}_{b\_B,c\_B}}$	1	1	0	0	1		
X_{31}	$\mathbf{Ww}_{c\_O,d\_O,\mathbf{w}_{c\_B,d\_B}}$	1	1	0	0	1		
X_{32}	$\mathbf{Hw}_{a\_A,b\_A}$	1	1	-0.1	1			
X_{33}	$\mathbf{Hw}_{b\_A,c\_A}$	1	1	-0.1	1			
X_{34}	$\mathbf{Hw}_{c\_A,d\_A}$	1	1	-0.1	1			
X_{35}	$\mathbf{Hw}_{a\_B,b\_B}$	1	1	-0.1	1			
X_{36}	$\mathbf{Hw}_{b\_B,c\_B}$	1	1	-0.1	1			
X_{37}	$\mathbf{Hw}_{c\_B,d\_B}$	1	1	-0.1	1			
X_{38}	$\mathbf{Hw}_{a\_O,b\_O}$	1						
X_{39}	$\mathbf{Hw}_{b\_O,c\_O}$	1						
X_{40}	$\mathbf{Hw}_{c\_O,d\_O}$	1						
X_{41}	$\mathbf{Mw}_{a\_A,b\_A}$	1	1	1	1	-1	-1	-1
X_{42}	$\mathbf{Mw}_{b\_A,c\_A}$	1	1	1	1	-1	-1	-1
X_{43}	$\mathbf{Mw}_{c\_A,d\_A}$	1	1	1	1	-1	-1	-1
X_{44}	$\mathbf{Mw}_{a\_B,b\_B}$	1	1	1	1	-1	-1	-1
X_{45}	$\mathbf{Mw}_{b\_B,c\_B}$	1	1	1	1	-1	-1	-1
X_{46}	$\mathbf{Mw}_{c\_B,d\_B}$	1	1	1	1	-1	-1	-1

Fig. 9. 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}	$\mathbf{W}_{a\_A,b\_A}$			1	
X_{18}	$\mathbf{W}_{b\_A,c\_A}$			1	
X_{19}	$\mathbf{W}_{c\_A,d\_A}$			1	
X_{20}	$\mathbf{W}_{a\_B,b\_B}$			1	
X_{21}	$\mathbf{W}_{b\_B,c\_B}$			1	
X_{22}	$\mathbf{W}_{c\_B,d\_B}$			1	
X_{23}	$\mathbf{W}_{a\_O,b\_O}$				1
X_{24}	$\mathbf{W}_{b\_O,c\_O}$				1
X_{25}	$\mathbf{W}_{c\_O,d\_O}$				1
X_{26}	$\mathbf{Ww}_{a\_O,b\_O},\mathbf{w}_{a\_A,b\_A}$			1	
X_{27}	$\mathbf{Ww}_{b\_O,c\_O},\mathbf{w}_{b\_A,c\_A}$			1	
X_{28}	$\mathbf{Ww}_{c\_O,d\_O},\mathbf{w}_{c\_A,d\_A}$			1	
X_{29}	$\mathbf{Ww}_{a\_O,b\_O},\mathbf{w}_{a\_B,b\_B}$			1	
X_{30}	$\mathbf{Ww}_{b\_O,c\_O},\mathbf{w}_{b\_B,c\_B}$			1	
X_{31}	$\mathbf{Ww}_{c\_O,d\_O},\mathbf{w}_{c\_B,d\_B}$			1	
X_{32}	$\mathbf{Hw}_{a\_A,b\_A}$	1			
X_{33}	$\mathbf{Hw}_{b\_A,c\_A}$	1			
X_{34}	$\mathbf{Hw}_{c\_A,d\_A}$	1			
X_{35}	$\mathbf{Hw}_{a\_B,b\_B}$	1			
X_{36}	$\mathbf{Hw}_{b\_B,c\_B}$	1			
X_{37}	$\mathbf{Hw}_{c\_B,d\_B}$	1			
X_{38}	$\mathbf{Hw}_{a\_O,b\_O}$	1			
X_{39}	$\mathbf{Hw}_{b\_O,c\_O}$	1			
X_{40}	$\mathbf{Hw}_{c\_O,d\_O}$	1			
X_{41}	$\mathbf{Mw}_{a\_A,b\_A}$	1			
X_{42}	$\mathbf{Mw}_{b\_A,c\_A}$	1			
X_{43}	$\mathbf{Mw}_{c\_A,d\_A}$	1			
X_{44}	$\mathbf{Mw}_{a\_B,b\_B}$	1			
X_{45}	$\mathbf{Mw}_{b\_B,c\_B}$	1			
X_{46}	$\mathbf{Mw}_{c\_B,d\_B}$	1			

Fig. 10. Role matrices for the aggregation characteristics: combination function weights.

mcfp	combination function parameters	1 alogistic		2 steponce		3 max-hebb		4 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}	$\mathbf{W}_{a\_A,b\_A}$					X_{41}			
X_{18}	$\mathbf{W}_{b\_A,c\_A}$					X_{42}			
X_{19}	$\mathbf{W}_{c\_A,d\_A}$					X_{43}			
X_{20}	$\mathbf{W}_{a\_B,b\_B}$					X_{44}			
X_{21}	$\mathbf{W}_{b\_B,c\_B}$					X_{45}			
X_{22}	$\mathbf{W}_{c\_B,d\_B}$					X_{46}			
X_{23}	$\mathbf{W}_{a\_O,b\_O}$							1	
X_{24}	$\mathbf{W}_{b\_O,c\_O}$							1	
X_{25}	$\mathbf{W}_{c\_O,d\_O}$							1	
X_{26}	$\mathbf{Ww}_{a\_O,b\_O},\mathbf{w}_{a\_A,b\_A}$							1	
X_{27}	$\mathbf{Ww}_{b\_O,c\_O},\mathbf{w}_{b\_A,c\_A}$							1	
X_{28}	$\mathbf{Ww}_{c\_O,d\_O},\mathbf{w}_{c\_A,d\_A}$							1	
X_{29}	$\mathbf{Ww}_{a\_O,b\_O},\mathbf{w}_{a\_B,b\_B}$							1	
X_{30}	$\mathbf{Ww}_{b\_O,c\_O},\mathbf{w}_{b\_B,c\_B}$							1	
X_{31}	$\mathbf{Ww}_{c\_O,d\_O},\mathbf{w}_{c\_B,d\_B}$							1	
X_{32}	$\mathbf{Hw}_{a\_A,b\_A}$	5	0.3						
X_{33}	$\mathbf{Hw}_{b\_A,c\_A}$	5	0.3						
X_{34}	$\mathbf{Hw}_{c\_A,d\_A}$	5	0.3						
X_{35}	$\mathbf{Hw}_{a\_B,b\_B}$	5	0.3						
X_{36}	$\mathbf{Hw}_{b\_B,c\_B}$	5	0.3						
X_{37}	$\mathbf{Hw}_{c\_B,d\_B}$	5	0.3						
X_{38}	$\mathbf{Hw}_{a\_O,b\_O}$	5	0.3						
X_{39}	$\mathbf{Hw}_{b\_O,c\_O}$	5	0.3						
X_{40}	$\mathbf{Hw}_{c\_O,d\_O}$	5	0.3						
X_{41}	$\mathbf{Mw}_{a\_A,b\_A}$	5	2						
X_{42}	$\mathbf{Mw}_{b\_A,c\_A}$	5	2						
X_{43}	$\mathbf{Mw}_{c\_A,d\_A}$	5	2						
X_{44}	$\mathbf{Mw}_{a\_B,b\_B}$	5	2						
X_{45}	$\mathbf{Mw}_{b\_B,c\_B}$	5	2						
X_{46}	$\mathbf{Mw}_{c\_B,d\_B}$	5	2						

Fig. 11. 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}	$\mathbf{W}_{a\_A,b\_A}$	X_{32}
X_{18}	$\mathbf{W}_{b\_A,c\_A}$	X_{33}
X_{19}	$\mathbf{W}_{c\_A,d\_A}$	X_{34}
X_{20}	$\mathbf{W}_{a\_B,b\_B}$	X_{35}
X_{21}	$\mathbf{W}_{b\_B,c\_B}$	X_{36}
X_{22}	$\mathbf{W}_{c\_B,d\_B}$	X_{37}
X_{23}	$\mathbf{W}_{a\_O,b\_O}$	X_{38}
X_{24}	$\mathbf{W}_{b\_O,c\_O}$	X_{39}
X_{25}	$\mathbf{W}_{c\_O,d\_O}$	X_{40}
X_{26}	$\mathbf{W}w_{a\_O,b\_O},w_{a\_A,b\_A}$	0.2
X_{27}	$\mathbf{W}w_{b\_O,c\_O},w_{b\_A,c\_A}$	0.2
X_{28}	$\mathbf{W}w_{c\_O,d\_O},w_{c\_A,d\_A}$	0.2
X_{29}	$\mathbf{W}w_{a\_O,b\_O},w_{a\_B,b\_B}$	0.2
X_{30}	$\mathbf{W}w_{b\_O,c\_O},w_{b\_B,c\_B}$	0.2
X_{31}	$\mathbf{W}w_{c\_O,d\_O},w_{c\_B,d\_B}$	0.2
X_{32}	$\mathbf{H}w_{a\_A,b\_A}$	0
X_{33}	$\mathbf{H}w_{b\_A,c\_A}$	0
X_{34}	$\mathbf{H}w_{c\_A,d\_A}$	0
X_{35}	$\mathbf{H}w_{a\_B,b\_B}$	0
X_{36}	$\mathbf{H}w_{b\_B,c\_B}$	0
X_{37}	$\mathbf{H}w_{c\_B,d\_B}$	0
X_{38}	$\mathbf{H}w_{a\_O,b\_O}$	0.9
X_{39}	$\mathbf{H}w_{b\_O,c\_O}$	0.9
X_{40}	$\mathbf{H}w_{c\_O,d\_O}$	0.9
X_{41}	$\mathbf{M}w_{a\_A,b\_A}$	0
X_{42}	$\mathbf{M}w_{b\_A,c\_A}$	0
X_{43}	$\mathbf{M}w_{c\_A,d\_A}$	0
X_{44}	$\mathbf{M}w_{a\_B,b\_B}$	0
X_{45}	$\mathbf{M}w_{b\_B,c\_B}$	0
X_{46}	$\mathbf{M}w_{c\_B,d\_B}$	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}	$\mathbf{W}_{a\_A,b\_A}$	0.1
X_{18}	$\mathbf{W}_{b\_A,c\_A}$	0.1
X_{19}	$\mathbf{W}_{c\_A,d\_A}$	0
X_{20}	$\mathbf{W}_{a\_B,b\_B}$	0
X_{21}	$\mathbf{W}_{b\_B,c\_B}$	0.1
X_{22}	$\mathbf{W}_{c\_B,d\_B}$	0.1
X_{23}	$\mathbf{W}_{a\_O,b\_O}$	0
X_{24}	$\mathbf{W}_{b\_O,c\_O}$	0
X_{25}	$\mathbf{W}_{c\_O,d\_O}$	0
X_{26}	$\mathbf{W}w_{a\_O,b\_O},w_{a\_A,b\_A}$	0
X_{27}	$\mathbf{W}w_{b\_O,c\_O},w_{b\_A,c\_A}$	0
X_{28}	$\mathbf{W}w_{c\_O,d\_O},w_{c\_A,d\_A}$	0
X_{29}	$\mathbf{W}w_{a\_O,b\_O},w_{a\_B,b\_B}$	0
X_{30}	$\mathbf{W}w_{b\_O,c\_O},w_{b\_B,c\_B}$	0
X_{31}	$\mathbf{W}w_{c\_O,d\_O},w_{c\_B,d\_B}$	0
X_{32}	$\mathbf{H}w_{a\_A,b\_A}$	0.05
X_{33}	$\mathbf{H}w_{b\_A,c\_A}$	0.05
X_{34}	$\mathbf{H}w_{c\_A,d\_A}$	0.05
X_{35}	$\mathbf{H}w_{a\_B,b\_B}$	0.05
X_{36}	$\mathbf{H}w_{b\_B,c\_B}$	0.05
X_{37}	$\mathbf{H}w_{c\_B,d\_B}$	0.05
X_{38}	$\mathbf{H}w_{a\_O,b\_O}$	0
X_{39}	$\mathbf{H}w_{b\_O,c\_O}$	0
X_{40}	$\mathbf{H}w_{c\_O,d\_O}$	0
X_{41}	$\mathbf{M}w_{a\_A,b\_A}$	0.995
X_{42}	$\mathbf{M}w_{b\_A,c\_A}$	0.995
X_{43}	$\mathbf{M}w_{c\_A,d\_A}$	0.995
X_{44}	$\mathbf{M}w_{a\_B,b\_B}$	0.99
X_{45}	$\mathbf{M}w_{b\_B,c\_B}$	0.99
X_{46}	$\mathbf{M}w_{c\_B,d\_B}$	0.99

Fig. 12. Role matrices **ms** for the timing characteristics (speed factors) and initial values **iv**.

A.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. 10.

In role matrix **mcfp** (see Fig. 11) 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 $\boldsymbol{\mu}$ represented by the self-model states X_{41} to X_{46}).

A.3. Role matrices for timing characteristics

In Fig. 12, 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 **W**-states X_{17} to X_{25} are represented by (second-order) self-model $\mathbf{H}_{\mathbf{W}}$-states X_{32} to X_{40}.

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