

An Adaptive Self-modeling Network Model for Multilevel Organizational Learning

Canbaloglu, Gülay ; Treur, J.; Roelofsma, P.H.M.P.

DOI

[10.1007/978-981-19-1610-6_16](https://doi.org/10.1007/978-981-19-1610-6_16)

Publication date

2022

Document Version

Final published version

Published in

Proceedings of 7th International Congress on Information and Communication Technology - ICICT 2022

Citation (APA)

Canbaloglu, G., Treur, J., & Roelofsma, P. H. M. P. (2022). An Adaptive Self-modeling Network Model for Multilevel Organizational Learning. In X.-S. Yang, S. Sherratt, N. Dey, & A. Joshi (Eds.), *Proceedings of 7th International Congress on Information and Communication Technology - ICICT 2022* (pp. 179-191). (Lecture Notes in Networks and Systems; Vol. 448). Springer Nature. https://doi.org/10.1007/978-981-19-1610-6_16

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

Green Open Access added to TU Delft Institutional Repository

'You share, we take care!' - Taverne project

<https://www.openaccess.nl/en/you-share-we-take-care>

Otherwise as indicated in the copyright section: the publisher is the copyright holder of this work and the author uses the Dutch legislation to make this work public.

An Adaptive Self-modeling Network Model for Multilevel Organizational Learning



Gülay Canbaloglu, Jan Treur, and Peter Roelofsma

Abstract Multilevel organizational learning concerns an interplay of different types of learning at individual, team, and organizational levels. These processes use complex dynamic and adaptive mechanisms. A second-order adaptive network model for this is introduced here and illustrated.

Keywords Multilevel organizational learning · Adaptive network model · Self-model

1 Introduction

Multilevel organizational learning is a complex, dynamic, adaptive, cyclical, and non-linear type of learning involving multiple levels and both dependent on individuals and independent of individuals. It is multilevel because the learning of an organization involves learning at the level of individuals, at the level of teams (or groups or projects), and at the level of the organization via feed forward and feedback pathways:

Through feed forward processes, new ideas and actions flow from the individual to the group to the organization levels. At the same time, what has already been learned feeds back from the organization to group and individual levels, affecting how people act and think. (Wiewiora et al. [5], p. 532)

G. Canbaloglu (✉) · J. Treur · P. Roelofsma
Delft University of Technology, Center for Safety in Healthcare, Delft, The Netherlands
e-mail: gcanbaloglu17@ku.edu.tr

J. Treur
e-mail: j.treur@vu.nl

P. Roelofsma
e-mail: P.H.M.P.Roelofsma@tudelft.nl

G. Canbaloglu
Department of Computer Engineering, Koç University, Istanbul, Turkey

J. Treur
Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

There is growing consensus in the literature that the theory of organizational learning should consider individual, team, and organizational levels. (Wiewiora et al. [15], p. 94)

There is a huge amount of literature on multilevel organizational learning such as [1, 3, 5, 7–9, 14, 15]. However, systematic approaches to obtain (adaptive) computational models for it cannot be found. In the current paper, a self-modeling network modeling perspective is used to model the different adaptive, interacting processes of multilevel organizational learning.

Computational modeling of multilevel organizational learning provides a more observable formalization of multilevel organizational learning and provides possibilities to perform “in silico” (simulation) experiments with it. To this end, the self-modeling network modeling approach introduced in Treur [10] that is explained in detail in Sect. 3 is used in this current paper.

First, Sect. 2 presents how literature provides ideas on mental models at individual, team, and organization level and their role in multilevel organizational learning. Then, Sect. 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. 4, the controlled adaptive network model for multilevel organizational learning is introduced. Then, in Sect. 5, an example simulation scenario is explained in detail. Section 6 is a discussion section.

2 Background Literature

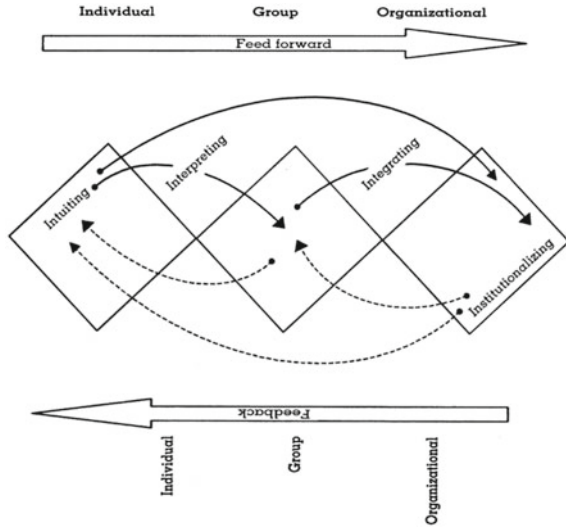
The quotes in the introduction section illustrate the perspective adopted here. Mental models are considered a vehicle to model the interplay of learning at individual, team, and organizational level. Individual mental models learnt are a basis for formation of shared team mental models; these shared team mental models provide input for the shared mental models at the organization level. Conversely, these shared mental models at organization and team level are used to improve shared team mental models and individual mental models, respectively. The picture of the different pathways shown in Fig. 1 is a slightly rearranged version of Fig. 1 in Crossan et al. [5] and also strongly resembles Fig. 4 of Wiewiora et al. [15] and Fig. 3 of Wiewiora et al. [14].

Inspired by this, as a basis for the analysis made here, the considered overall multilevel organizational learning process consists of the following main processes and interactions; see also [5] and Wiewiora et al. [15]:

(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

Fig. 1 Dynamics of organizational learning; adapted from Crossan et al. [5], Fig. 1. For a similar picture, see Wiewiora et al. [15], Fig. 4 and Fig. 3 of Wiewiora et al. [14]



- (b) **From individual level to team level (feed forward learning)**
 - (1) Deciding about creation of shared team mental models
 - (2) Creating shared team mental models based on developed individual mental models
- (c) **From team level to organization level (feed forward learning)**
 - (1) Deciding about creation of shared mental models
 - (2) Creating shared mental models based on developed individual mental models
- (d) **From organization level to team level (feedback learning)**
 - (1) Deciding about teams to adopt shared organization mental models
 - (2) Teams adopting shared mental models
- (e) **From team level to individual level (feedback learning)**
 - (1) Deciding about individuals to adopt shared team mental models
 - (2) Individuals adopting shared team mental models by learning them
- (f) **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

This overview provided useful input to the design of the computational network model for multilevel organizational learning that will be introduced in Sect. 4.

3 The Self-modeling Network Modeling Approach

In this section, the self-modeling modeling approach [11] used is explained. A network model is defined by (where X and Y are nodes or states of the network):

- *Connectivity characteristics*

Connections from one state X to a state Y with their weights $\omega_{X,Y}$

- *Aggregation characteristics*

For any state Y , a combination function $cc_Y(\cdot)$ is used to specify the aggregation that is applied to the impacts $\omega_{X,Y}X(t)$ on Y from the incoming connections from states X to Y

- *Timing characteristics*

For each state Y , a speed factor η_Y defines how fast it changes for given causal impact.

The following difference equations are used for simulation; they are based on the network characteristics $\omega_{X,Y}$, $c_Y(\cdot)$, η_Y in a canonical manner:

$$Y(t + \Delta t) = Y(t) + \eta_Y [c_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) - Y(t)]\Delta t \quad (1)$$

for each state Y , where X_1 to X_k are the states from which Y receives incoming connections. The dedicated software environment [11, Chap. 9] includes a library with currently around 50 basic combination functions. The examples of basic combination functions that are applied in the model introduced here can be found in Table 1.

By a *self-modeling network* (also called a *reified* network), a network-oriented conceptualization can also be applied to *adaptive* networks; see Treur [10]. Here, new states are added to the network (called *self-model states*) representing network characteristics. These self-model states are depicted at a next level (called *self-model level* or *reification level*); the original network is at the *base level*.

This is often applied to the weight $\omega_{X,Y}$ of a connection from state X to state Y ; this is represented by a self-model state $W_{X,Y}$. Similarly, any other network characteristic from $\omega_{X,Y}$, $c_Y(\cdot)$, η_Y can be self-modeled by including self-model states. For example, a speed factor η_Y can be represented by a self-model state H_Y .

This self-modeling network construction can 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 $H_{w_{X,Y}}$ representing the speed factor $\eta_{w_{X,Y}}$ for the (learning) dynamics of

Table 1 The combination functions applied 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 $_{\alpha,\beta}(..)$	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 states X and Y ; V_3 activation level of the self-model state $W_{X,Y}$ Persistence factor μ
Maximum composed with Hebbian learning	max-hebb $_{\mu}(V_1, \dots, V_k)$	$\max(\text{hebb}_{\mu}(V_1, V_2, V_3), V_4, \dots, V_k)$	
Scaled maximum	smax $_{\lambda}(V_1, \dots, V_k)$	$\max(V_1, \dots, V_k)/\lambda$	Scaling factor λ

first-order self-model state $W_{X,Y}$ which in turn represents the adaptation of connection weight $\omega_{X,Y}$. Similarly, a persistence factor $\mu_{w_{X,Y}}$ of such a first-order self-model state $W_{X,Y}$ used for adaptation (e.g., based on Hebbian learning) can be represented by a second-order self-model state $M_{w_{X,Y}}$.

In the current paper, the self-modeling network perspective is applied to design 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 models the control over this; see Fig. 2. In this way, the three-level cognitive architecture described in Treur and Van Ments [11], Van Ments et al. [13]

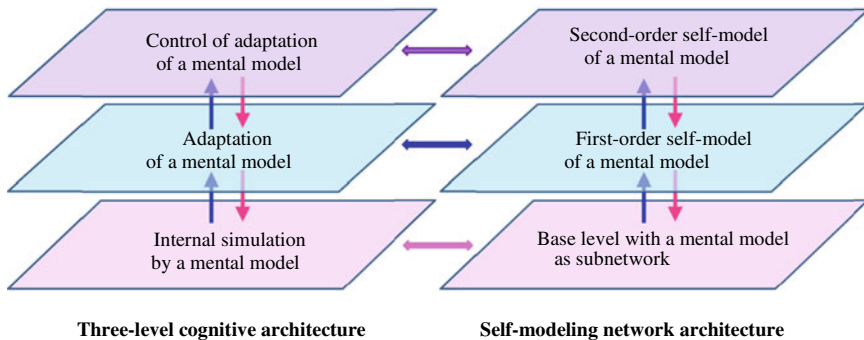


Fig. 2 Computational formalization of the three-level cognitive architecture for mental model handling from Van Ments et al. [12] by a self-modeling network architecture

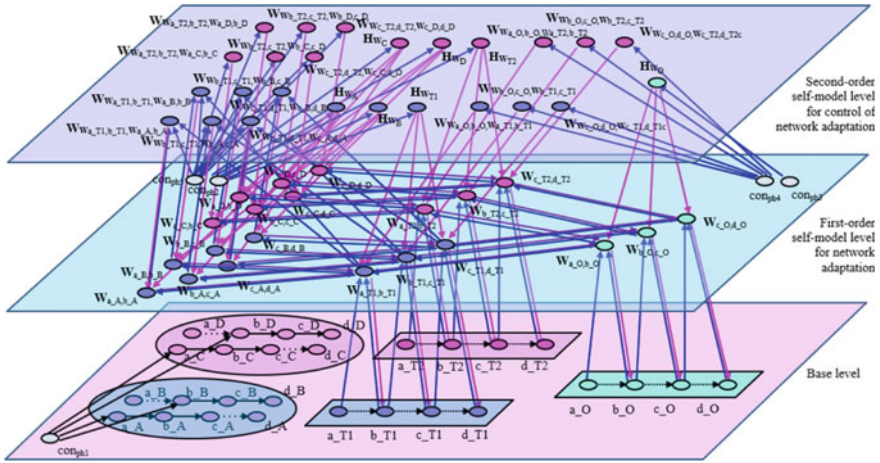


Fig. 3 Connectivity of the second-order adaptive network model for the second-order self-model of the mental models: the interactions between the first-order self-model level and the second-order self-model level: the second-order Hebbian learning for the second-order W -states (the W_W -states)

is formalized computationally in the form of a self-modeling network architecture. In Bhalwankar and Treur [2], it is shown how specific forms of learning and their control can be modeled based on this self-modeling network architecture, in particular learning by observation and learning by instruction and combinations thereof Yi and Davis [16], Van Gog et al. [12]. Some of these forms of learning will also be applied in the model for multilevel organizational learning introduced here in Sect. 4.

4 The Network Model for Organizational Learning

In the considered case study concerning tasks a , b , c , and d , initially, the individual mental models of 4 people are different and based on some strong and some weak connections; they do not use a stronger shared mental model as that does not exist yet. The multilevel organizational learning addressed to improve the situation covers:

1. Individual (Hebbian) learning by persons of their mental models through internal simulation which results in stronger but still incomplete and different mental models. Person A and C’s mental models have no connection from task c to task d , and person B and D’s mental models have no connection from a to b .
2. Formation of two shared team mental models for teams T1 (consisting of persons A and B) and T2 (consisting of persons C and D) based on the different individual mental models. A process of unification by aggregation takes place (feed forward learning).

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_C	Individual mental model state for person C for task a
X ₁₀	b_C	Individual mental model state for person C for task b
X ₁₁	c_C	Individual mental model state for person C for task c
X ₁₂	d_C	Individual mental model state for person C for task d
X ₁₃	a_D	Individual mental model state for person D for task a
X ₁₄	b_D	Individual mental model state for person D for task b
X ₁₅	c_D	Individual mental model state for person D for task c
X ₁₆	d_D	Individual mental model state for person D for task d
X ₁₇	a_T1	Shared mental model state for team T1 for task a
X ₁₈	b_T1	Shared mental model state for team T1 for task b
X ₁₉	c_T1	Shared mental model state for team T1 for task c
X ₂₀	d_T1	Shared mental model state for team T1 for task d
X ₂₁	a_T2	Shared mental model state for team T2 for task a
X ₂₂	b_T2	Shared mental model state for team T2 for task b
X ₂₃	c_T2	Shared mental model state for team T2 for task c
X ₂₄	d_T2	Shared mental model state for team T2 for task d
X ₂₅	a_O	Shared mental model state for organization O for task a
X ₂₆	b_O	Shared mental model state for organization O for task b
X ₂₇	c_O	Shared mental model state for organization O for task c
X ₂₈	d_O	Shared mental model state for organization O for task d
X ₂₉	con _{ph1}	Context state for Phase 1: individual mental model simulation and learning
X ₃₀	con _{ph2}	Context state for Phase 2: creation of shared mental models for teams T1 and T2
X ₃₁	con _{ph3}	Context state for Phase 3: creation of a shared mental model for organization O
X ₃₂	con _{ph4}	Context state for Phase 4: learning shared team mental models from the shared mental model for organization O
X ₃₃	con _{ph5}	Context state for Phase 5: learning individual mental models from the shared mental models for teams T1 and T2
X ₃₄	con _{ph6}	Context state for Phase 6: individual mental model simulation and learning

Fig. 4 Base level states of the introduced adaptive network model

3. Formation of a shared organization mental model based on the two team mental models. Again, a process of unification by aggregation takes place (feed forward learning).
4. Flow of information and knowledge from organization mental model to team mental models, e.g., a form of instructional learning (feedback learning).
5. Learning of individual mental models from the shared team mental models, e.g., also a form of instructional learning (feedback learning).
6. Improvements on 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 and C's mental models have a connection from task c to task d, and person B and D's mental models have a connection from a to b.

The connectivity of the introduced network model is shown in Fig. 3; for an overview of the states, see Figs. 4 and 5, and for more details about the connections and how they relate to (a) to (f) from Sect. 2, see the Appendix stored as Linked Data at URL <https://www.researchgate.net/publication/354352746>.

The undermost base level of this model has mental model states for individuals, teams and organization, and also context states for activation of six different phases (like the (a) to (f) in Sect. 2.3) at different times. The mental states of persons are connected to each other according to the order of the tasks, and the first ones have a

Nr	State	Explanation
X35	$W_{a,A,b,A}$	First-order self-model state for the weight of the connection from a to b within the individual mental model of person A
X36	$W_{b,A,c,A}$	First-order self-model state for the weight of the connection from b to c within the individual mental model of person A
X37	$W_{c,A,d,A}$	First-order self-model state for the weight of the connection from c to d within the individual mental model of person A
X38	$W_{a,B,b,B}$	First-order self-model state for the weight of the connection from a to b within the individual mental model of person B
X39	$W_{b,B,c,B}$	First-order self-model state for the weight of the connection from b to c within the individual mental model of person B
X40	$W_{c,B,d,B}$	First-order self-model state for the weight of the connection from c to d within the individual mental model of person B
X41	$W_{a,C,b,C}$	First-order self-model state for the weight of the connection from a to b within the individual mental model of person C
X42	$W_{b,C,c,C}$	First-order self-model state for the weight of the connection from b to c within the individual mental model of person C
X43	$W_{c,C,d,C}$	First-order self-model state for the weight of the connection from c to d within the individual mental model of person C
X44	$W_{a,D,b,D}$	First-order self-model state for the weight of the connection from a to b within the individual mental model of person D
X45	$W_{b,D,c,D}$	First-order self-model state for the weight of the connection from b to c within the individual mental model of person D
X46	$W_{c,D,d,D}$	First-order self-model state for the weight of the connection from c to d within the individual mental model of person D
X47	$W_{a,T1,b,T1}$	First-order self-model state for the weight of the connection from a to b within the shared mental model of team T1
X48	$W_{b,T1,c,T1}$	First-order self-model state for the weight of the connection from b to c within the shared mental model of team T1
X49	$W_{c,T1,d,T1}$	First-order self-model state for the weight of the connection from c to d within the shared mental model of team T1
X50	$W_{a,T2,b,T2}$	First-order self-model state for the weight of the connection from a to b within the shared mental model of team T2
X51	$W_{b,T2,c,T2}$	First-order self-model state for the weight of the connection from b to c within the shared mental model of team T2
X52	$W_{c,T2,d,T2}$	First-order self-model state for the weight of the connection from c to d within the shared mental model of team T2
X53	$W_{a,O,b,O}$	First-order self-model state for the weight of the connection from a to b within the shared mental model of the organisation O
X54	$W_{b,O,c,O}$	First-order self-model state for the weight of the connection from b to c within the shared mental model of the organisation O
X55	$W_{c,O,d,O}$	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. 5 First-order self-model states of the introduced adaptive network model

connection from first context state to be able to start to perform internal simulation and learn. As can be seen in Fig. 3, some connections between task states of persons are dashed, which means initially there is no connection. Therefore, states where these dashed connections are, are the “hollow” non-known mental states of persons. These states have connections from a fifth context state to enable to observe the improvement of individual with the impact of organization and team mental models in Phase 5. The base level mental states relate to the basic tasks and can be considered as the basic ingredients of the mental models representing knowledge on relations between tasks.

To make the mental models adaptive, first-order self-model states are added in the intermediary level. These are \mathbf{W} -states representing adaptive weights for each developed connection of individual, team, and organization mental states in the base level. There are also intralevel \mathbf{W} -to- \mathbf{W} connections between first-order \mathbf{W} -states here to provide feed forward learning in Phase 2 and Phase 3 and feedback learning in Phase 4 and Phase 5 [5]. These \mathbf{W} -to- \mathbf{W} connections correspond to the arrows for feed forward and feedback learning shown in Fig. 1.

Formation of shared team and organization mental models is performed by this feed forward learning mechanism, and the learning from the shared organization mental model and the shared team mental model by individuals occurs by the feedback learning mechanism.

To control this adaptivity in first-order adaptation level, second-order self-model states are added in the uppermost level. In first place, there are $\mathbf{W}_\mathbf{W}$ -states (higher-order \mathbf{W} -states) for (intralevel) connections between first-order adaptivity level \mathbf{W} -states, in other words, adaptive weight representation of the connections of adaptive weight representation states in the level below. These control processes are left out of consideration in Fig. 1 based on Crossan et al. [5] and Wiewiora et al. [15] but still are crucial for the processes to function well. Additionally, $\mathbf{H}_\mathbf{W}$ -states for adaptation speeds of connection weights in the first-order adaptation level and $\mathbf{M}_\mathbf{W}$ -states for persistence of adaptation are placed here. This provides the speed and persistence control of the adaptation. For a full specification of the network model, see linked data at <https://www.researchgate.net/publication/354352746>.

5 Example Simulation Scenario

In this scenario, for reasons of presentation, a multi-phase approach is applied to get a clear picture of the progress of multilevel organizational learning via teams. In general, the model can also process all phases simultaneously. It is possible to see the feed forward flow of the development of shared team mental models from individual mental models first, formation of the shared organization mental model originating from teams’ mental models, then and finally, by the feedback flow, the impact of these shared mental models on teams and individuals. In practice and also in the model, these phases also can overlap or take place entirely simultaneously. The considered six phases are as follows:

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

This relates to (a) in Sect. 2. Different individual mental models by four different persons are constructed and strengthened here. The knowledge levels of people for the tasks, initially, are not same. Thus, the learning levels are different as can be seen in the first phase between time 25 and 200 in the simulation graph in Fig. 6. For example, activation levels of first three base state for tasks *a* to *c* of person A from Team 1 and person C from Team 2 (*a_A* to *c_A* and *a_C* to *c_C*) increase while the activation levels of states for task *d* (*d_A* and *d_C*) remain at zero indicating that they do not have knowledge on this task. A similar lack of knowledge is observed for the other persons B from Team 1 and D from Team 2, for task *a* this time. Therefore, the activation levels of their states *a_B* and *a_D* remain at zero in this phase, while others get increased (*b_B* to *d_B* and *b_D* to *d_D*). After this first individual learning phase, forgetting takes place for all persons because they do not have perfect persistence factors self-model *M*-state values (values < 1, meaning imperfection). Increased

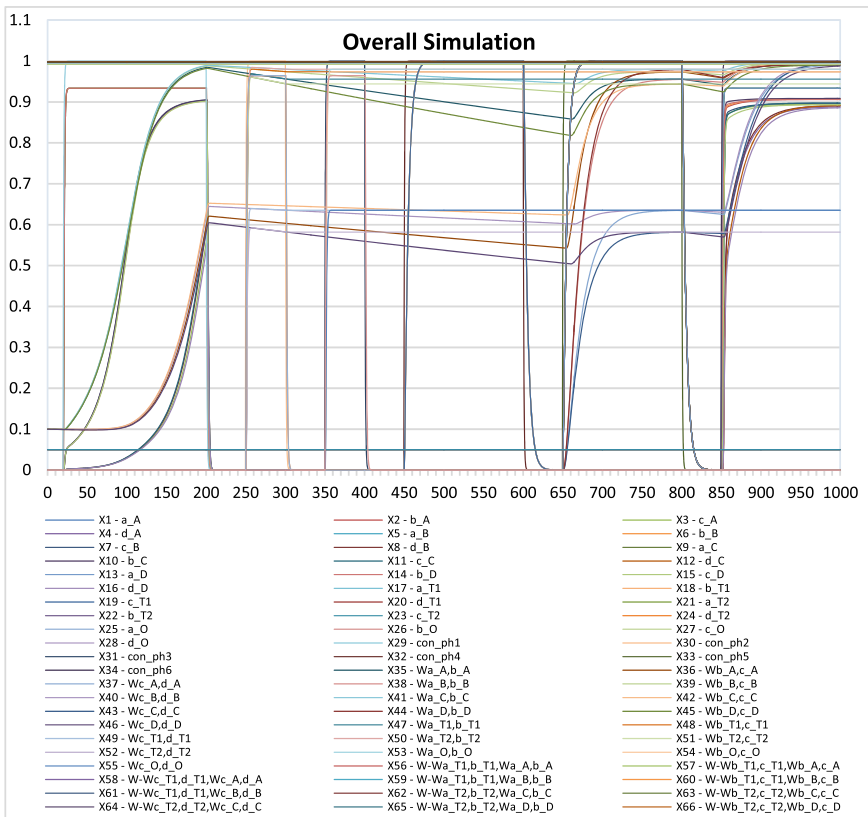


Fig. 6 Simulation graph showing all states

W-states during phase 1, start to slightly decrease after phase 1 at different rates representing the differences between persons concerning forgetting speed.

- **Phase 2: Shared team mental model formation (feed forward learning)**

This relates to **(b)** in Sect. 2. Formation of two shared team mental models happens in this phase. The collaboration of the individuals creates the aggregation of their mental models as part of feed forward organizational learning (in this case team learning). The **W**-states of the teams ($\mathbf{W}_{a_{T1},b_{T1}}$ to $\mathbf{W}_{c_{T1},d_{T1}}$ and $\mathbf{W}_{a_{T2},b_{T2}}$ to $\mathbf{W}_{c_{T2},d_{T2}}$) increase at different rates in Phase 2 between time 250 and 300 in Fig. 6. Team 1 becomes better at the connection $c \rightarrow d$, and Team 2 becomes better at connection $a \rightarrow b$ because the teams have different persons. Then, these shared mental models are maintained by the two teams.

- **Phase 3: Shared organization mental model formation (feed forward learning)**

This relates to **(c)** in Sect. 2. A shared organization mental model is formed in this phase from the unification and aggregation of the two shared team mental models. The values of shared organization mental model **W**-states ($\mathbf{W}_{a_{O},b_{O}}$ to $\mathbf{W}_{c_{O},d_{O}}$) increase here between time 350 and 400.

- **Phase 4: Feedback learning of the shared team mental model from the shared organization mental model**

This relates to **(d)** in Sect. 2. Knowledge from the shared organization mental model is received by the team mental models as a form of (instructional) feedback learning here in this phase. The (higher-order adaptive) connections from organization **W**-states to teams **W**-states (X_{68} to X_{73}) become activated, and the teams start to get stronger connections about tasks.

- **Phase 5: Feedback learning of the individual mental models from the shared team mental models**

This relates to **(e)** in Sect. 2. Improved knowledge from shared team mental models is received by individuals as a form of (instructional) feedback learning in this phase. Higher-order adaptive weight states for connections from teams **W**-states to individual **W**-states (X_{56} to X_{67}) are activated. This provides the learning of individual mental models and gives persons the chance of improving their unknown connections in the next phase. For instance, the person A starts to learn about the task d that it does not know in the beginning by the help of its team. In Fig. 6, the **W**-states of persons make jumps in this Phase 5 between time 650 and 800.

- **Phase 6: Individual mental model usage and learning**

This relates to **(f)** in Sect. 2. Persons start to further improve their knowledge and skills (their mental models) already strengthened in Phase 5 by Hebbian learning [6]. Person A's knowledge on task d (state d_A) becomes nonzero now (obtained

via shared team mental model), and similar improvements are observed for other persons and their “hollow” unknown states.

6 Discussion

Within mainstream organizational learning literature such as Crossan et al. [5], Wiewiora et al. [15], mental models at individual, team, and organization levels and the interplay of them are considered to be a vehicle for organizational learning. This is called multilevel organizational learning. Based on developed individual mental models, by so-called feed forward learning, the formation of shared team mental models can take place and based on them, a shared mental model for the level of the organization as a whole (see also Fig. 1 adopted from the mentioned literature). Once these shared mental models have been formed, they can be adopted by individuals within the organization, indicated as feedback learning. This involves a number of mechanisms of different types that by their cyclical interaction together can be considered to form the basis of multilevel organizational learning. These mechanisms have been formalized in a computational manner here and brought together in an adaptive self-modeling network architecture. The model was illustrated by a relatively simple but realistic case study. For the sake of presentation, in the case study scenario, the different types of mechanisms have been controlled in such a manner that they are sequentially over time. This is not inherent in the designed computational network model: these processes can equally well work simultaneously. The two lowest levels of the three-level network model describe Fig. 1 very well, especially the intralevel connections within the middle level directly correspond to the arrows in Fig. 1. However, the necessary control of these processes is left out of consideration in Fig. 1 but is fully addressed here by the highest (third) level. For many more details about this modeling approach for multilevel organisational learning, see also the forthcoming book [4].

One of the 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 maximal knowledge about a specific mental model connection. But other forms of aggregation can equally well be applied, for example, weighted averages. Another possible extension is to make states used for the control adaptive in a context-sensitive manner, 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.

References

1. Argyris C, Schön DA (1978) Organizational learning: a theory of action perspective. Addison-Wesley, Reading, MA

2. Bhalwankar R, Treur J (2021) Modeling learner-controlled mental model learning processes by a second-order adaptive network model. *PLoS One* 16(8):e0255503
3. Bogenrieder I (2002) Social architecture as a prerequisite for organizational learning. *Manag Learn* 33(2):197–216
4. Canbaloglu G, Treur J, Wiewiora A (eds) (2023) Computational modeling of multilevel organisational learning and its control using self-modeling network models (to appear). Springer Nature
5. Crossan MM, Lane HW, White RE (1999) An organizational learning framework: from intuition to institution. *Acad Manag Rev* 24:522–537
6. Hebb DO (1949) *The organization of behavior: a neuropsychological theory*. Wiley, New York
7. Kim DH (1993) The link between individual and organisational learning. *Sloan Manag Rev* 1993:37–50
8. McShane SL, von Glinow MA (2010) *Organizational behavior*. McGraw-Hill (2010)
9. Stelmaszczyk M (2016) Relationship between individual and organizational learning: mediating role of team learning. *J Econ Manag* 26(4):1732–1947. <https://doi.org/10.22367/jem.2016.26.06>
10. Treur J (2020) Network-oriented modeling for adaptive networks: designing higher-order adaptive biological, mental and social network models. Springer Nature, Cham
11. Treur J, Van Ments L (eds) (2022) *Mental models and their dynamics, adaptation, and control: a self-modeling network modeling approach*. Cham Switzerland, Springer Nature
12. Van Gog T, Paas F, Marcus N, Ayres P, Sweller J (2009) The mirror neuron system and observational learning: implications for the effectiveness of dynamic visualizations. *Educ Psychol Rev* 21(1):21–30
13. Van Ments L, Treur J, Klein J, Roelofsma PHMP (2021) A second-order adaptive network model for shared mental models in hospital teamwork. In: *Proceedings of ICCCI'21, Lecture Notes in AI*, vol 12876. Springer Nature, pp 126–140
14. Wiewiora A, Chang A, Smidt M (2020) Individual, project and organizational learning flows within a global project-based organization: exploring what, how and who. *Int J Project Manage* 38:201–214
15. Wiewiora A, Smidt M, Chang A (2019) The ‘How’ of multilevel learning dynamics: a systematic literature review exploring how mechanisms bridge learning between individuals, teams/projects and the organization. *Eur Manag Rev* 16:93–115
16. Yi MY, Davis FD (2003) Developing and validating an observational learning model of computer software training and skill acquisition. *Infor Syst Res* 14(2):146–169